It's Not All About the Music:

Digital Goods, Social Media, and the Pressure of Peers

by

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ABSTRACT

Social media offers a powerful platform for the independent digital content producer community to develop, disperse, and maintain their brands. In terms of information systems research, the broad majority of the work has not examined hedonic consumption on Social Media Sites (SMS). The focus has mostly been on the organizational perspectives and utilitarian gains from these services. Unlike through traditional commerce channels, including e-commerce retailers, consumption enhancing hedonic utility is experienced differently in the context of a social media site; consequently, the dynamic of the decision-making process shifts when it is made in a social context. Previous research assumed a limited influence of a small, immediate group of peers. But the rules change when the network of peers expands exponentially. The assertion is that, while there are individual differences in the level of susceptibility to influence coming from others, these are not the most important pieces of the analysis—unlike research centered completely on influence. Rather, the context of the consumption can play an important role in the way social influence factors affect consumer behavior on Social Media Sites. Over the course of three studies, this dissertation will examine factors that influence consumer decision-making and the brand personalities created and interpreted in these SMS. Study one examines the role of different types of peer influence on consumer decision-making on Facebook. Study two observes the impact of different types of producer message posts with the different types of influence on decision-making on Twitter. Study three will conclude this work with an exploratory empirical investigation of actual twitter postings of a set of musicians. These studies contribute to the body of IS literature by evaluating the specific behavioral changes related to

consumption in the context of digital social media: (a) the power of social influencers in contrast to personal preferences on SMS, (b) the effect on consumers of producer message types and content on SMS at both the profile level and the individual message level.

DEDICATION

To my mother and father. Without whom I, quite literally, would not be here.

And to James T. Kirk, who taught me to never believe in the “no-win scenario.”

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"…if you are an indie musician who is NOT utilizing social networking to promote your music and increase your fan base, you are cutting yourself off at the knees."

-ArtistDevelopmentBlog

Chapter 1

INTRODUCTION

Social media offers a tremendous opportunity for those willing to harness the power of the community to develop, disperse, and maintain their brands. Since the dot-com bubble burst, we have seen Social Media Sites (SMS) such as MySpace, Facebook, and Twitter emerge and recapture the excitement with technology among consumers (CBS 2012; SEC 2011). Facebook stands out as a clear favorite among these sites growing from a mere 1 million users in December 2004 to 1.11 billion registered users, as of May 2013 (AP 2013). And there is clearly no indication that this exponential growth will slow anytime soon. In fact, the company reported Q1 2013 revenues of $1.46 billion, up from the $1.06 billion from Q1 2012 (SEC 2013; Sengupta 2013).

Research regarding the phenomenon of Social Media has covered a broad range of topics across varying research disciplines from Psychology to Education to Management, examining subjects such as Social Capital (Ellison et al. 2007), User Generated Content (Rui and Whinston 2011; Susarla et al. 2011), Human Behavior and Relations (Moore and McElroy 2011), Ethnicity and Higher Education (Lewis et al. 2008), Corporate Business Value (Culnan et al. 2010), and Cloud Computing (Henderson 2010), to name a few. More recent works in this area have explored the evolution of user-generated content, word of mouth, and Human-Computer Interactions (Gallaugher and

Ransbotham 2010; Ong and Day 2010; Sung et al. 2010; Susarla et al. 2011; Tang et al. 2012). SMS research has only recently begun to expand into the evaluation of digital goods markets, especially in relation to hedonic consumption, or consuming a good as an experiential product related to "the multisensory, fantasy, and emotive aspects of one's experience with products" (Hirschman and Holbrook 1982; Lacher 1989)

In terms of information systems research, a majority of the work has not focused on the hedonic utility gains from individuals using SMS. The focus for researchers has been on the organizational perspectives and utilitarian gains from SMS (Agarwal et al. 2008; Chellappa and Saraf 2010; Culnan et al. 2010; Sasidharan et al. 2011; Sykes et al. 2009). While there has been IS research surrounding consumer behavior, these works have not often enforced hedonic consumption in the context of social media engagement as their driving focus (Ho et al. 2011; Pavlou and Fygenson 2006; Xiao and Benbasat 2007).

Normally, when we make decisions to consume a good that increases our hedonic utility (e.g., an MP3 album, a digital movie, etc.), we make this decision in private. We seek information from our peers and we sample content, but we typically make the final purchase decision alone. An SMS such as Facebook changes that dynamic significantly. Now our decisions are made with the eyes of our "community" upon us (Bateman et al. 2011; Bearden and Etzel 1982). There is no anonymity. As such, with the gaze and judgment of others looming over them, consumers have a strong tendency to adjust behavior to conform to the group's expectations. Thus, the assertion driving this research is that hedonic utility, the overall personal benefits from the experience of a good (Babin et al. 1994; Overby and Lee 2006), is enhanced differently in the context of a social network.

Ultimately, the decision-making process surrounding hedonic consumption may follow a different set of rules on something like Facebook than it would with a normal merchant, even a digital retailer. On the demand side, the social process that dictates this behavior is typically referred to as normative or *peer influence* (Park and Lessig 1977). This stands in contrast to *informational influences* which are self-imposed, as individuals research products and services before making the decision to finally purchase (Bearden et al. 1989; Deutsch and Gerard 1955). On the supply side, digital content producers can utilize different *social media messaging strategies* to more effectively engage with their prospective consumers. On an SMS like Twitter, this could be something as simple as how often messages are sent to followers, if the message more personal or more informational, or whether the messages utilize service mechanisms (hashtags, urls, etc.) in a way that stimulates engagement with users (Donath and Boyd 2004; Huberman et al. 2008; Naaman et al. 2010).

Digital music is a prime context for examining social antecedents of hedonic consumption. In a series of informal discussions with a few small groups of undergraduate freshmen at Arizona State University on the subject of using Facebook to find new music and musicians, a small number of themes emerged across all groups with amazing frequency: students felt that “liking” an artist on Facebook was less about an interest in music and finding new artists and more about creating a perception that your friends and others would have about you. Most students felt that access to audio of a song was better than video of a song. But, more than anything, students wanted to feel a personal connection to the artists they choose to follow on Social Media Sites: “it wasn’t always about the music.”

1.1. Research Questions

The overarching goal of this research is to examine the factors that potentially drive consumers to engage with digital goods producers on Social Media Sites. We have seen research and opinion outlining the different “currencies” contributing to overall social capital on SMS (Coleman 1988; Resnick 2001), the consensus falling on two different areas: tie strength (Borgatti and Cross 2003; Granovetter 1973; Levin and Cross 2004) and the “Like”/”follow” found on Facebook and Twitter, respectively (Egebark and Ekström 2011; Mulvihill 2011; Raszl 2011). So how do digital content producers effectively leverage these Social Media Sites to drive engagement with consumers of their goods and services?

The power of social networks lies not only in the artificial currencies established as constructs of the network itself, but in how people communicate and interact with one another. We’ve seen an abundance of research on how we conduct ourselves in the role of the consumer in traditional commerce, even e-commerce, but we have yet to see a robust discussion on how we conduct ourselves as consumers in a 21st Century *social commerce* context. The nature of these networks has a direct effect on how we choose to represent ourselves and how we wish to be seen and judged by our peers. This represents a golden opportunity for content producers to reach these consumers in a new way. This is of special import to independent producers, who lack the large outreach and marketing mechanisms that traditionally accompany large organizations.

The goal for this research is to evaluate how independent digital content producers can more effectively communicate with and influence choice for consumers on Social Media Sites. To this end, we seek to address the following questions: (1) How do different types of social influence change consumer behavior toward independent digital content producers on Social Media Sites? And (2) What type of social media messaging strategies can independent digital content producers employ to positively impact the identity they seek to create? These questions serve to help producers utilize modern social commerce channels to reach consumers and potentially gain access to their network of weak-ties. These indie producers, who cannot rely on the traditional marketing and communications channels exploited by content producers with the backing of large companies, can apply this information to formulate an effective strategy to navigate the waters of the evolving 21st Century digital economy.

Chapter 2

RESEARCH BACKGROUND AND REVIEW

2.1. Introduction

The research offered in this dissertation examines the role of *influencers* and *messaging* on the relationship between digital content producers and consumers in the context of Social Media Sites. This section provides a brief overview of and the related areas discussed in this research. Each paradigm is expanded upon and offered context as each study is presented in the following chapters. In the following sections, we introduce the context of this research: (1) independent musicians, serving as the digital content producers of interest, and (2) the Facebook and Twitter Social Media Sites, which currently represent the largest and most rapidly growing social media platforms. We then present the theoretical foundations that these studies are built upon: social influence and word of mouth in electronic commerce.

2.2. Context

2.2.1. Digital Music

Due to advancements in technology in the last ten years that have allowed for digital representations of traditionally physical good, digital goods markets have been steadily on the rise. Examples of these changes have been observed in media platforms such as movies, music, software distribution, and books. The music industry has served as a rich base for research into the behavior and evolution of digital goods markets (Bhattacharjee et al. 2003; Bockstedt et al. 2006; Gopal and Sanders 2006; Levy and Bosteels 2010; Van der Beek et al. 2005); the context for this research is the independent ("indie") music market. Traditionally, the music industry has seen a static division in the major players, with the majority of sales coming from the “big four” record labels and the remainder from indie sources. According to Nielsen SoundScan (2008), the market share breakdown for 2008 was as follows: Universal Music Group (UMG) had a market share of 31.5%; Sony BMG had 25.3%; the Warner Music Group (WMG) controlled 21.4%; *indie sources accounted for 12.8%;* and EMI had the remaining 9%. “Indie sources,” in this case, is a catch all term for music that is not published by UMG, Sony, Warner, or EMI. In this context, our analysis will focus on indie musicians who lack formal representation in the traditional sense and the power of consumer outreach that comes with large-scale organizational infrastructure.

2.2.2. Social Media

Extant research has shown that recommender systems and online user communities are among the most important aspects of e-commerce (Au and Kauffman 2008; Bakos 2001; Zhu and Zhang 2010). Not only are consumers able to locate the products they are looking for with greater speed and efficiency, new markets allow for strong communities of users and active/passive recommendation systems, which empower customers to find products they may not have known they were seeking (Brynjolfsson and Smith 2003). In more recent years, Social Media Sites have moved to the forefront for analysis of the impact of user communities on electronic commerce (Bennett et al. 2008; Bonhard and Sasse 2006; Constantinides and Fountain 2008; Stephen and Toubia 2010; Swamynathan et al. 2008).

Social Media has been defined as “a group of Internet-based applications […] which allows the creation and exchange of user-generated content.” (Kaplan and Haenlein 2010; Kwahk and Ge 2012). Taken in light of how digital content producers have been disintermediating the traditional distribution channels, moving closer to their intended consumer base (Bockstedt et al. 2006), and the sustained reliability of recommender systems and reviews (Bakos 2001; Stephen and Toubia 2010), we see new types of word of mouth arise in the form of *social commerce* platforms (Brynjolfsson and Smith 2000; Brynjolfsson and Smith 2003; Kwahk and Ge 2012; Stephen and Toubia 2010). Facebook and Twitter are two platforms of particular relevance to this research.

Facebook

Facebook is a network structure that allows users to post status updates, commentaries, photographs, videos, etc. with their connected network of "friends." Beginning in 2004, Facebook has grown well beyond initial expectation, sporting 3.66 billion daily page views from its 850+ million worldwide members (CBS 2012; Womack 2012). The mechanism of interest on Facebook is the notion of the "Like." If a user finds a post or a photograph or, most importantly, a company, product, and/or service interesting, they can click the ubiquitous "Like" button that broadcasts their interest in said item on their Facebook "wall" for their friends and friends' friends to see and comment upon.

Much of the extant literature on Facebook usage has examined psychological implications, use patterns, as well as identity and privacy concerns (Golder et al. 2007; Gross and Acquisti 2005; Lampe et al. 2007; Stutzman 2006). What is less explored in the literature are the ways in which *social commerce* players can effectively leverage support or information-seeking activities to drive engagement with digital content producers. This engagement has the potential to drive sales of their content.

Twitter

Twitter is a short messaging service that rapidly broadcasts messages of up to 140 characters, called *tweets*, to a group of interconnected individuals, identified as "followers." Twitter has quickly exploded as one of the most popular and effective social networking platforms, boasting over 500 million registered users as of early 2012 (Dugan 2012). Twitter functions through the mechanism of "tweeting" messages out to a user's followers which can, in turn, be rebroadcast or "retweeted" to followers.

The key difference between the Facebook and Twitter SMS are the active vs. passive manner of dissemination of information in addition to the availability of rich media available on specific users' pages. Facebook allows for rich media as well as robust dialogue and communication. Twitter, on the other hand, is purely for the dissemination of information (links to media can be included in the message); the Tweets themselves are nothing but raw text, up to 140 characters. Furthermore, Facebook posts information (ex. _____ liked _____) passively, with little user control over the information that is sent out by default. This is in contrast to tweets on Twitter, which do not go out without specific, active participation by the user (Bakshy et al. 2011b; Huberman et al. 2008).

2.3. Theoretical Perspectives

Researchers have studied the phenomena of recommender systems and digital community structures as e-commerce has grown and matured over the last fifteen years (Au and Kauffman 2008; Bakos 2001; Zhu and Zhang 2010). We've seen the distance between producers and consumers reduced in light of significantly reduced search costs and disintermediation of the traditional market value chain (Bakos 2001; Bockstedt et al. 2006; Brynjolfsson and Smith 2003). As time has gone on and technology has pushed forward, we've seen SMS moving to the frontlines in terms of evaluating digital commerce community structures and the evolution of new forms of word of mouth. This has created a new form of social media fueled e-commerce known as *social commerce* (Bennett et al. 2008; Bonhard and Sasse 2006; Brynjolfsson and Smith 2000; Brynjolfsson and Smith 2003; Constantinides and Fountain 2008; Kwak et al. 2010; Stephen and Toubia 2010; Swamynathan et al. 2008).

The key theoretical areas that serve as the basis of this research are that of social influence and word of mouth and their ultimate impact on consumer choice in the context of Social Media Sites, as outlined above. Social influence research seeks to identify whether or not people's opinions and behaviors have any sort of impact on the opinions and behaviors of other people. Of specific interest to this research is the impact of social influence in the context of *social commerce* by way of traditional and electronic commerce.

The widely accepted constructs for evaluating interpersonal influence are: *informational influence*, *value expressive* (aka *peer*) *influence*, and *utilitarian influence*; the latter two are often, sometimes questionably, aggregated as *normative influence* (Bearden and Etzel 1982; Bearden et al. 1989; Burnkrant and Cousineau 1975; Deutsch and Gerard 1955; Moschis and Churchill Jr 1978; Park and Lessig 1977). *Informational influence* is the active seeking of information from other people, often product experts, in order to influence the decision-making process. *Informational influence* is the active seeking of information from other people, often product experts, in order to influence the decision-making process (Deutsch and Gerard 1955). *Value expressive/peer influence* is an alteration of one's own behavior based on observations of the behavior of people with whom they share a relationship (Park and Lessig 1977). While *utilitarian/normative influence* is an *a priori* adjustment of behavior based upon what they perceive and/or anticipate others might expect or demand of them (Bearden et al. 1989).

In a social media context, influence can be reflected in an examination of the effect of word of mouth (WOM) on consumer intentions and behavior. WOM is the viral nature of communication between consumers at each stage of the purchase decision, coming into stark focus in the information-gathering phases of decision-making (Liu 2006; Mahajan et al. 1984; Van den Bulte and Lilien 2001). In recent years, the impact of WOM on adoption/purchase behavior has become far easier to study due the emergence of electronic word of mouth (eWOM) channels such as user reviews, forums, and other recommender systems (Dwyer 2007; Godes and Mayzlin 2004; Hennig-Thurau et al. 2004). Personality has also been shown as a strong driver of usage and influence on social networking platforms, personality being an individual's (a) level of activity on Facebook, (b) the number of "friends" they boast, and (c) the nature of the messages posted to a Facebook wall or Twitter feed (Dann 2010; Moore and McElroy 2011; Naaman et al. 2010; Rui and Whinston 2011).

The consensus on WOM is that it can have a significant impact on attitude and intention among consumers (Griffin and Hauser 1993; Richins 1983). Of particular interest is the specific impact of negative word of mouth (NWOM) which, in the form of negative reviews and comments related to unfavorable experiences, can have a profoundly deleterious impact on a producer or service provider's reputation, brand equity, and sales (Keller 1993; Keller 2003; Luo and Bhattacharya 2006; Singh 1988). Recent research has shown that NWOM's effect is not just short-term drops in brand equity and sales, but rather is “more destructive in magnitude, kicking in quickly and affecting investors longer” (Luo 2006; Luo and Bhattacharya 2006).

2.4. Summary and Conclusions

The key differences in SMS platforms like Twitter and Facebook allow for a rich evaluation of the role of different types of social influences as well as the content of information presented by different users. In the context of *social commerce*, these sites are the perfect test bed for evaluating how content producers can effectively leverage the network to drive engagement with the potential consumers of their respective products, which is increasingly difficult in independent, niche markets.

In this section we outlined Social Media Sites and how they have been previously identified and utilized in Information Systems research. We offered specific focus on the Facebook and Twitter SMS which are not only the largest Social Media Sites in the world today, but they also serve to have the largest impact on behavioral norms, which in turn have a profound impact on consumer behavior in electronic commerce. We then gave an overview of the research foundations, social influence, word of mouth, and their potential impact on consumer decision-making. These will be further contextualized and expanded upon in the studies examined in Chapters 3-5.

Chapter 3

"THIS IS OURSELVES UNDER PRESSURE": SOCIAL INFLUENCES ON USER PREFERENCE FOR MUSICIANS ON FACEBOOK

3.1. Introduction

Word of mouth (WOM), the viral dissemination of information and opinion is a powerful driver of behavior, especially in regards to consumer decision-making (Dellarocas 2003; Dellarocas et al. 2007; Liu 2006). This has become a more profound influencer of social behavior as the world has become more digitized, interconnected, and well informed, as has been demonstrated by the power of social networks and social media platforms (Godes and Mayzlin 2004; Hennig-Thurau et al. 2004; Jansen et al. 2009). Yet consumers still tend to regard themselves as independent thinkers. They like to gather enough information until they feel that they are able to make a decision related to their personal preferences and the utility that will be generated by the outcome of this specific decision. For instance, when buying a new music album alone, people generally know their preferences toward specific types of music and take the time to read reviews of a new album from professionals, perhaps listen to a few samples, and then make their decision on whether or not to buy the album. However, the dynamic of this decision-making process shifts when it is made in a social context.

The extant SMS research in IS literature has predominantly focused on the organizational perspectives and utilitarian gains from employing SMS services (Agarwal et al. 2008; Chellappa and Saraf 2010; Culnan et al. 2010; Sasidharan et al. 2011; Sykes et al. 2009). Some studies have demonstrated the impact that social buying has on the decision-making process when the consumer was subjected to the limited influence of a small, immediate group of peers (Bearden and Etzel 1982; Childers and Rao 1992; Park and Lessig 1977). These studies examined consumer behavior in relation to influence when their peers were actively and physically present. What happens when the network of observing peers expands exponentially, such as on a social network like Facebook? Not only do we see the network of peers expand on SMS, we also see their presence become one that is perceived rather than actually observed. This phenomenon on communications networks is typically referred to as differing levels of *social presence* (Kumar and Benbasat 2006; Short et al. 1976). One of the key observations of group influence research is that the more visible someone's behavior is in a well-defined group structure, the more responsive that person will be to the influences of the group (Aral and Walker 2011a; Aral and Walker 2011b; Deutsch and Gerard 1955; Park and Lessig 1977).

This study contributes to and complements this existing body of research by examining social buying, specifically the role of *informational* and *social influencers*, in the context of *social commerce*. We examine these influencers and their effect on driving SMS engagement with digital content producers, in this case, digital musicians. This study further examines these influencers and the ways in which they interact with personal characteristics, specifically *social presence* and *susceptibility to social influence*, to generate the expression of personal hedonic utility gains.

3.2. Perspective and Research Questions

In an effort to study further the notion of engagement and consumption in a social media context, we sought to examine the factors that influence a person's decision to consume a good that increases their overall hedonic utility. We aim to answer the following research questions: (1) How do peer and informational influence impact consumer choice on Facebook? (2) Does positive influence counteract the effect of negative influence? (3) Are these effects moderated by a user's susceptibility to social influences and their feelings of social presence on Facebook? The key dependent variable is a person's decision—whether or not to "Like" the provider of the digital good (in our context, music). When a person evaluates the Facebook page of a musician with whom he/she is not familiar, he/she generally want to sample some of the music offered and consider opinions and judgments of his/her peers before making the final decision to click "Like." The decision to "Like" is then broadcast on the person's Facebook page, informing friends and other weakly connected groups of people. Hedonic and social values are linked in this evaluation of individual preference and social influences.

To address these research objectives, we utilized a controlled experimental setting involving undergraduate business school students. The dependent variable of interest in our study is the respondents' decision to "Like" a musician or group of musicians on Facebook when shown (a) the artist's Facebook page, (b) a sample of their music, and (c) comments from peers and professional reviewers. The results from the experiment indicate that, while personal preference plays a major role in which artists to "Like," Peer and Informational Influences have a significant impact on the ultimate decision. Key to understanding the full impact of influencer effects is the evaluation of the moderating effect of strong feelings of Social Presence on Informational Influence; when feelings of Social Presence on Facebook are included in the analysis, we see a significant elevation in the impact of Informational Influence on the decision to "Like." This study demonstrates that the *context* of consumption plays an important role even in the presence of peer and informational influence factors that affect consumer behavior on Social Media Sites. We find that while personal preference still matters, online consumption behavior is affected by these unique characteristics of Social Media Sites, causing consumers to alter their decisions to consume digital goods that, under different circumstances, they may otherwise not partake.

3.3. Hypotheses and Research Model

3.3.1. The Meaning of "Like"

Our variable of interest is the user's decision to click the ubiquitous "Like" button on the Facebook page of a digital musician. What is the impact and the meaning of this action? Studies surrounding social contagion and viral/word-of-mouth marketing have shown that passive broadcasting on social networking platforms, such as an automatic wall post stating you clicked on the "Like" button on a product/service's Facebook page, produce a 246% increase in the rate of adoption of the product or service by the friends of the person who initially "Liked" the page, demonstrating a clear potential impact of peer influence/social contagion effect (Aral and Walker 2011a; Aral and Walker 2011b; comScore 2011). Recently, market research has sought to evaluate how the specific Facebook "Like" converts to actual sales of products. The research has found that Facebook users who "Liked" BlackBerry on Facebook were 5.6 times more likely to purchase their devices and had an 87% probability of actively recommending the device to their friends. On the other hand, owners who did not "Like" the company had only a 44% probability of recommending Blackberry to their friends (Forrester 2012).

Clearly there is potential in the “Like” to be leveraged by sellers and producers of goods. Not only in the direct effect it can have on the user, but also on the connected members of their community on a SMS.

3.3.2. Social Influence

External, *social influence* addresses the predilection people have toward others influencing their behavior. It runs the gamut from colloquial (“If everyone was jumping off the Brooklyn Bridge, would you do it too?”), to questions of economics (Manski 2000), to serious life and death questions (Gardner and Steinberg 2005). Ultimately, the question of external influence in any context is “do the actions and opinions of some drive the actions and opinions of others?”

Bearden et al. (1989) developed a two-dimensional scale for measuring interpersonal influence in consumers based on the assertions of Deutsch and Gerard (1955) that interpersonal influence is manifested through either normative or informational influences. They describe *informational* peer influence as being rooted in a person’s “tendency to accept information from others as evidence about reality” (Deutsch and Gerard 1955). We particularly see examples of this in a consumer context: people seeking reviews/evaluations of a product or service (e.g., Amazon.com reviews) before making a purchase. This occurs in both active and passive manners (Bearden et al. 1989). We therefore predict that informational influence will play a role in shaping music consumers’ preferences.

H1 (Facebook Informational Influence Hypothesis)

Informational Influence will impact the decision to “Like” a musician on Facebook

Research has defined normative influence as a pairing of *value expressive* and *utilitarian influences* (Burnkrant and Cousineau 1975; Deutsch and Gerard 1955): value expressive being the adoption of behavior based on the observation of others with whom the consumer shares a close personal relationship (Park and Lessig 1977) while utilitarian influence is observed in a person conforming to what they perceive others demand of them, either for personal gratification or to avoid punishment (Bearden et al. 1989; Moschis and Churchill Jr 1978; Park and Lessig 1977).

The common evaluation of normative influence conflates value expressive influence and utilitarian influence, despite utilitarian being *a priori* and value expressive being *a posteriori.* The implication of "normative" behavior is that people are conforming their behavior to what they perceive to be the expected behavioral norms of the group (Asch 1952; Festinger 1953; Lascu and Zinkhan 1999). This is *a priori* behavior based on utilitarian influence. *A posteriori* conformity, or value expressive influence, is decision-making in the presence of knowledge of the group choices and preferences. This is more accurately identified as peer pressure, social influence or *peer influence* (Bearden and Etzel 1982; Park and Lessig 1977). We intend to measure the effect that peer influence has on the decision-making process of music consumers on the Facebook SMS.

H2 (Facebook Peer Influence Hypothesis)

Peer Influence will impact the decision to "Like" a musician on Facebook

It is unclear whether peer and informational influences interact. Theoretically, the underlying processes for the two influences are distinct. While peer influence is a response to the group by the individual geared toward enhancing social standing, informational influence is driven through an evaluation mechanism without regard for the impact of the decision on the individual's standing in the group. Therefore, it is quite possible that informational and peer influences are complementary. That is, individuals may see positive informational influences as additional inputs in their decision-making process. As such, we expect to see a positive interaction effect of informational and peer influences.

H3 (Facebook Social Influence Interactions Hypothesis)

Peer Influence and informational influence will jointly impact the decision to "Like" a musician on Facebook

Given the intensely personal nature of social networking sites and the direct relation to interpersonal relationships, we cannot discount the impact of utilitarian influence observed when a person conforms to the perceived behavioral norms of their immediate and weakly-connected social circles (Bearden and Etzel 1982; Park and Lessig 1977); the implication of this is the adjustment of behavior to avoid punishment and/or achieve personal gratification (Asch 1952; Festinger 1953; Lascu and Zinkhan 1999). Bearden et al. (1989) developed a series of self-reporting measures to determine an individual's *influence susceptibility*, or how likely interpersonal influencers are to adjust their behavior; these influencers being the established informational, value expressive, and utilitarian social influences.

We refer to the measure of how much a medium enables people to create a personal connection with their peers as *social presence* (Short et al. 1976). The importance of social presence on SMS has to do with the appearance of one's peers being present, if only virtually (Fulk et al. 1987). Social presence has been evaluated, in particular, in the context of online shopping. Given that Internet shopping can be a feel isolated and cold or sterilized, social presence has become an important metric for success, enhancing the experience that people have with others in a collective sense (Kumar and Benbasat 2006; Schubert 2000). Most of the research surrounding the phenomenon of social presence in the context of e-commerce and electronic communications has evaluated this effect in an active manner, i.e. you are shopping with a group of friends or you are communicating across a network with the full knowledge of your peers being present (Karahanna and Straub 1999; Kumar and Benbasat 2006; Zhu et al. 2010). However, in the context of SMS, social presence becomes a more passive effect; in the sense that your friends are sharing in experiences with you but are not experiencing the moment with you in real time (Cheung et al. 2011; Kaplan and Haenlein 2010). Of particular interest is how social presence affects the impact of peer and informational influencers on a user's decision-making regarding digital goods on SMS.

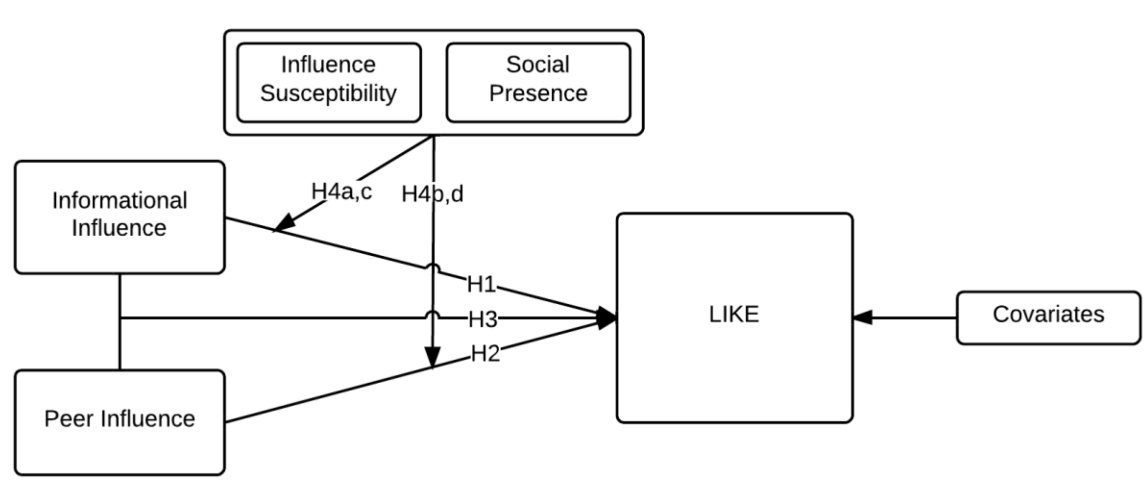
It stands to reason that the more a consumer (a) is initially susceptible to the judgments of others or (b) feels the presence of their peers while they are making consumption decisions that could potentially impact the way in which they are viewed, then the more their behavior will adjust in the presence of social influences. Using accepted measures, we will test the effect that susceptibility to influence and feelings of social presence have on the potential impact of peer and informational influencers on decision-making in the context of Social Media Sites. As our intent is to examine how these two phenomena affect influencers differently, we evaluate their moderating effect separately on each influence type.

H4 (Facebook Moderators Hypothesis)

a. **Influence Susceptibility will moderate the effect of Informational Influence on the decision to "Like" a musician on Facebook**
b. **Influence Susceptibility will moderate the effect of Peer Influence on the decision to "Like" a musician on Facebook**
c. **Social Presence will moderate the effect of Informational Influence on the decision to "Like" a musician on Facebook**
d. **Social Presence will moderate the effect of Peer Influence on the decision to "Like" a musician on Facebook**

Figure 1 presents the research model evaluated in this study. In the controlled experiment designed to test this research model, we evaluate two levels of influence: positive and negative, for *peer* and *informational influence* as well as their interaction. In addition to these main effects, we evaluate the impact of *influence susceptibility* and *social presence* on the effect of peer and information influences. We describe the experimental setting in the next section.

Figure 1. Research Model



3.4. Study Design

The experiment, presented in Table 1, uses a 2 (Peer Influence (PI): Negative (0) and Positive (1)) x 2 (Informational Influence (II): Negative (0) and Positive (1)) mixed design (Keppel 1991; Norman and Streiner 2003). Four repeated measures of "Like" were gathered for each subject, as explained below.

Table 1. 2x2 Experiment Design

	Informational Influence	
Peer Influence	[A] Negative Informational (II = 0) Negative Peer (PI = 0)	[B] Positive Informational (II = 1) Negative Peer (PI = 0)
	[C] Negative Informational (II = 0) Positive Peer (PI = 1)	[D] Positive Informational (II = 1) Positive Peer (PI = 1)

We first conducted a pilot study using the influence factors measured not against one another, but rather against varying *media richness* levels presented on musicians' Facebook pages. The results indicated that *peer influence* and *social presence* demonstrated a positive main effect on the user's decision to "Like" but media richness had no significant impact. These results and the feedback from the pilot study led to minor refinements in designing the manipulations and instruments employed in this current study. Subjects did not find any meaningful variance in media richness between the different musicians' Facebook pages and expressed preference to listen to the music sample than to watch a video of the musician. Therefore, we dropped media richness as a treatment variable from the main study. The data gathered during the Round 1 surveys, outlined in the following section, was also used to establish a baseline of "Likes" from a referent peer group similar to our intended population of interest. This baseline data, as reported here, was also utilized in the initial pilot study.

3.4.1. Round 1 – Baseline

The descriptive statistics for the baseline data recorded during round 1 are listed in Table 2.

Table 2. Survey Round 1 Covariates				
N	750			
Age	18:		226 (30%)	
	19:		212 (28%)	
	20-21:		298 (40%)	
	>21:		14 (2%)	
Gender	Male:		384 (51%)	
	Female:		366 (49%)	
Ethnicity	Caucasian (=0):		467 (62%)	
	African-American (=1):		40 (5%)	
	Hispanic (=2):		100 (13%)	
	Indian (=3):		18 (2%)	
	Asian (=4):		82 (11%)	
	Native American (=5):		11 (1%)	
	Other (=6)		32 (4%)	
# of FB Friends	Min: 5	Max: 3,910	Mean: 527.24	Median: 477
# of FB Hours (week)	Min: 0.5	Max: 150	Mean: 14.81	Median: 14
Genre Preference	Rock (=1): 269—36%			
	Pop (=2): 126—17%			
	Rap (=3): 251—33%			
	Country (=4): 96—13%			
	NR: 8—1%			

Given that the study measures the direct impact of peer influences, a baseline of “Likes” and comments was required to give students a strong sense of the feelings of their immediate peers. For this, an initial survey was conducted to evaluate the preferences for a specific series of musicians' Facebook pages. A group of 762 undergraduate Information Systems students was shown a selection of four musicians' Facebook pages across four different genres (pop, rock, country, and rap—all insignificantly correlated or even negatively correlated (Pachet and Cazaly 2000; Rentfrow and Gosling 2003)), each with clips of video and audio featuring their music. They were played a selection of two, two-minute media clips from each artist's page. During this time, the artist's Facebook page was left open on the screen while they listened/watched the clips. After each artist's selections were complete, the students were asked to evaluate whether or not they would choose to "Like" this artist and to provide a brief reason why, in their own words. They finished by answering a set of demographic and Facebook usage questions.

The data are reported after clean up and omission of some observations. Specifically, we excluded respondents who reported their age as less than 18 or who reported zero for their number of hours per week spent on and/or the number of friends they have on Facebook. These numbers would indicate they are not actual Facebook users or have not accurately reported their own information on the survey. The results from round 1 are presented in Table 3.

Table 3. Survey Round 1 Results

Artist	**Genre**	**Number of "Likes" on Facebook**	**Number of "Likes" in Round 1**
The Shins (A1)	Pop	499,066	425 (57%)
Buckcherry (A2)	Rock	383,555	295 (39%)
Kevin Fowler (A3)	Country	226,282	359 (48%)
Gangstagrass (A4)	Rap	28,782	112 (15%)

Patterns of "LIKE" in this baseline study reveals an implicit test of the peer influence effect. Each student in the 762-subject sample was shown all four artists, with no influence treatment conditions. There was also an implied peer influence factor, as the subjects were shown the artist's Facebook page throughout the time the media clip was playing, showing the number of "Likes" for that artist from the Facebook community at large. It is interesting to note that the number of "Likes" from the students closely mirrors those of the actual Facebook likes, albeit on a different order of magnitude. While there appears to be an impact from implicit peer influence here, there are no direct treatments being applied, so no conclusions can be adequately drawn from this observation.

3.4.2. Round 2 – To Like or Not to Like

For the actual study groups (distinct from the subjects from round 1), we utilized undergraduate university students in a major business school as respondents. Similar to the baseline study, the experimental context was explained to the participant(s), at which time they answered a series of questions to determine their preferences across a wide array of music genres (Pachet and Cazaly 2000; Rentfrow and Gosling 2003), which included the four genres of interest (pop, rock, country, rap); their self-reported Facebook usage; as well as some basic demographic information to serve as covariates. They were next shown the Facebook pages and media samples for each of the four artists (to control for and avoid the potential confounding effect of genre preference) in each of the experiment settings, holding PI and II constant across each artist for each subject. After showing each page and experiencing the sample music, respondents were asked whether they would choose to "Like" the particular artist. Each respondent also was asked to fill in two questions that served as manipulation checks: "One of the comments I saw for this artist was…" and a selection of comments from each of the varying levels of influence, only one of which would be correct for their response group. The process was repeated for the remaining artists. Finally, they were presented with a series of questions on a seven-point Likert scale to measure *influence susceptibility* and *social presence*.

Peer Influence

For *peer influence* (PI), the information collected during the first round of baseline surveys was presented alongside the Facebook page(s) and media clips. Changes in the peer influence factor involved the type of information revealed to the subjects about peer opinions regarding that particular musician. Depending on the survey treatment group, respondents were shown either positive (PI=1) or negative (PI=0) comments drawn from the baseline and the pilot study. The key point here is that the comments shown are coming explicitly from a referent peer group. To further enhance this point, the respondents were informed explicitly that they were seeing comments from their peer group.

Informational Influence

For the informational influence, we showed comments from a selection of professional reviewers, representing the exact type of information sought out during the decision-making process when shopping online. Similar to the peer influence treatment, depending on the group in which the students were placed, they were shown a series of subjective comments and scores from professional critics, either positive (II=1) or negative (II=0). Given that these artists are "independent musicians" and exist predominantly in the niche markets of the long tail of digital goods, these reviews were collected from a broad array of professional reviewers drawn from Internet publications and blogs.

Covariates

Aside from basic demographic information, we collected the respondents' perceptions about the network around them; specifically related to the degree they feel the presence of their network within Facebook and how often they engage with and may be influenced by this network, as well as how this artist's page may evoke a sense of a personal experience for them. We also included a measure to gauge their disposition toward independent vs. "superstar" artists. Additionally we collect respondents experience in playing a musical instrument in an ensemble or band. These questions are intended to control for involvement in music.

For measuring predisposition to *influence susceptibility*, we used a measure adapted from Park and Lessig (1977) and Bearden et al. (1989). These measures follow the same two levels of the peer influence construct in the main effects but allow the user to self-report their own feelings on how these factors may be dealt with in a generic context. This is largely to allow the subject to tell us how predisposed they may be to influence susceptibility overall. To measure *social presence* we adapted the measure from Kumar and Benbasat (2006), which was an extension of methods in Karahanna and Straub (Karahanna and Straub 1999) and Short et al. (1976).

Measures for respondents' likelihood to recommend and listen to each artist were also recorded. These measures are adopted from Oliver and Swan's (1989) interpretation of the *Customer Satisfaction Scale* and Zeithaml et al's (1996) *Loyalty Intent Scale* (Arens and Rust 2012; Oliver and Swan 1989; Zeithaml et al. 1996).

These measures, as described above, are presented in Appendix B. A sample of positive and negative comments, for both peer and informational influence, are also shown in Appendix C.

3.5. Results and Analysis

A total of 265 respondents participated in the final experiment. From these, we obtained 184 usable and completed surveys. Observations were initially omitted for (1) respondents who self-reported that they are under the age of eighteen, (2) subjects reporting zero or null for the number of Facebook friends, and (3) subjects reporting zero or null for the number of hours per week spent using the Facebook SMS. A key response in the survey pertained to subjects understanding of Facebook messaging. We omitted respondents who answered true to the final statement regarding messaging on Facebook, as described in Table 5. The biggest group of responses dropped pertained to respondents who did not fill in responses to the manipulation check questions. The 37 respondents who did not respond to these questions at all were ultimately omitted from the analysis since their responses may have biased the findings. These students either did not fully understand what was required of them during the experiment or may not have been paying sufficient attention to accurately represent the conditions being tested in our experiment. Finally, we omitted responses from subjects that demonstrated a lack of interest in responding to the survey questions— e.g., respondents reporting all 7s or 1s for every construct. Descriptive statistics from the final experiment are shown in Table 4.

Table 4. Descriptive Statistics

N	183 [A] = 56 [B] = 43 [C] = 33 [D] = 51
Age	18: 51 (28%) 19: 18 (10%)

	20-21: >21:		60 (32%) 54 (30%)	
Gender	Male: Female:		119 (65%) 64 (35%)	
Ethnicity	Caucasian (=0): African-American (=1): Hispanic (=2): Indian (=3): Asian (=4): Native American (=5): Other (=6)		129 (70%) 4 (2%) 15 (8%) 1 (1%) 31 (17%) 0 (0%) 3 (2%)	
# of FB Friends	Min: 25	Max: 5000	Mean: 500.25	Median: 400
# of FB Hours (week)	Min: 0.5	Max: 70	Mean: 7.51	Median: 5
Indie Preference	Min: 1	Max: 5	Mean: 2.64	
Play an Instrument?	Yes: No:		113 (62%) 70 (38%)	
Been in a Band?	Yes: No:		73 (40%) 110 (60%)	
Genre Preference	**Rock (1): 119—65%** **Pop (2): 109—60%** **Rap/Hip-Hop (3): 112—61%** **Country (4): 61—33%** Heavy Metal (5): 26—14% Soundtracks (6): 50—27% Soul/Funk (7): 24—13% Folk (8): 21—11%		Alternative (9): 113—62% Classical (10): 61—33% Electronic/Dance (11): 92—50% Religious (12): 9—5% Blues (13): 27—15% Jazz (14): 38—21% Other (15): 28—15%	

While distribution of ages is in accordance with expectations for the study population, the sample is disproportionately male and Caucasian. And though we collected preferences for various genres, the genres of interest were aligned with the four artists sampled (POP, ROCK, COUNTRY, RAP). These reported preferences were aligned with their reported choice of LIKE for each artist (LIKE_POP, LIKE_ROCK, LIKE_COUNTRY, LIKE_RAP) to generate a series of controls related to matching genre preference to Like (GENRE_MATCH_POP—GENRE_MATCH_RAP) as well as their reported preference for Independent artists compared to “superstar” artists—those represented by one of the Big Five record labels (INDIE).

Table 5. Meaning of “Like” Responses					
Statement		**True**		**False**	
1	**My “Like” gets registered on the person/company’s Facebook page**	215	85%	39	15%
2	**My “Like” gets posted on my Facebook Wall**	210	83%	44	17%
3	**By default, my “Like” gets posted on my friends’ timelines**	115	45%	139	54%
4	**I get updates on my timeline from that person/company**	190	75%	64	25%
5	**By default, my “Like” gets posted on the timeline of friends of friends**	46	18%	208	82%
6	**I get money from the person/company I chose to “Like”**	6	2%	248	98%

Table 5 presents the results from the students’ self-reported beliefs about the effects occurring when they click “Like” on Facebook. Market research has demonstrated that a startling majority of individuals (approx. 63%) do not adjust their Facebook privacy settings to control the amount of information supplied to the site and related applications (ConsumerReports 2012), with some research even reporting people find Facebook’s privacy settings to be “more confusing than credit card bills” (Palis 2012; Siegel+Gale 2012). Research has found that users who have stronger feelings of understanding and clarity regarding transparent and accessible privacy policies for sites and services are more willing to participate and commit to their retailer or service provider (Hui et al. 2007; Tsai et al. 2011). To this end, to better ensure the validity of our results, we collected information regarding the students' beliefs surrounding the potential impact of their decision to "Like" something/someone on Facebook.

According to the most current Facebook privacy settings, all messages and activities on Facebook are recorded on the user's timeline (formerly "wall") as well as the timeline of all associated friends and networks. Facebook identifies this setting as "Public" and accounts default to public for all messages; given this, the correct response to questions 1-5 is "true." Statements 1, 2 and 4 are commonplace among all but the most restrictive Facebook privacy settings and statement 6 is absurd, at best, serving as a check if the subjects are attentive to the answers they are providing in our experiment. Subsequently, any subjects reporting "true" in response to statement 6 have been omitted from our final analysis.

The specific comments of interest are 3 and 5. These directly address the subject's (a) comprehension of the meaning of "Like" and (b) awareness of the social penetration of their decision. From this we see that a significant proportion of students are not aware of how deeply into their network of weak ties their decision to "Like" something/someone on Facebook progresses. The perception being that they feel "Like" is less social than it exists in reality. One inference that could potentially be drawn from this is that if people were more familiar with the potential consequences of "Liking" something on Facebook, they may be influenced even more by external opinions, both from their peers and from professional informational sources. Put simply, there is a potential that our results may be biased downward.

Table 6. Marginal Means and the Effect of PI and II on LIKE
ARTIST_POP

	0	1	t
Peer Influence (PI)	0.6061	0.6310	**-0.3435**
Info. Influence (II)	0.5730	0.6596	**-1.2021**
ARTIST_ROCK			
Peer Influence (PI)	0.2222	0.2558	**-0.9839**
Info. Influence (II)	0.2022	0.2979	**-1.4914****
ARTIST_COUNTRY			
Peer Influence (PI)	0.2222	0.4881	**-3.9065*****
Info. Influence (II)	0.3034	0.3830	**-1.1306**
ARTIST_RAP			
Peer Influence (PI)	0.2121	0.2976	**-1.3278***
Info. Influence (II)	0.1798	0.3191	**-2.1888*****
LIKE (Total)			
Peer Influence (PI)	0.3157	0.4256	**-3.0926*****
Info. Influence (II)	0.3146	0.4149	**-2.8266*****
		***** p < 0.01**	**** p < 0.05 * p < 0.10**

Table 6 demonstrates the marginal means in each treatment cell across all four artists, representing the within-subjects factor (ARTIST_POP, ARTIST _ROCK, ARTIST _COUNTRY, ARTIST _RAP), as well as the marginal means for the overall dependent variable (LIKE). The cell means, aggregated in Table 6, for the overall DV (LIKE) are represented graphically in Figure 2. It is apparent from the means and t-tests reported in Table 6 that we see initial evidence that both influencers, PI and II, have a significant main effect on a user's decision to click LIKE for the artists; this provides encouragement that further analysis will reveal support for H1 and H2. We also do not observe any interaction effects (PI x II) across these different categories and treatments, leading us to believe H3 will not be supported.

Figure 2. Effect of PI and II on LIKE for All Artists

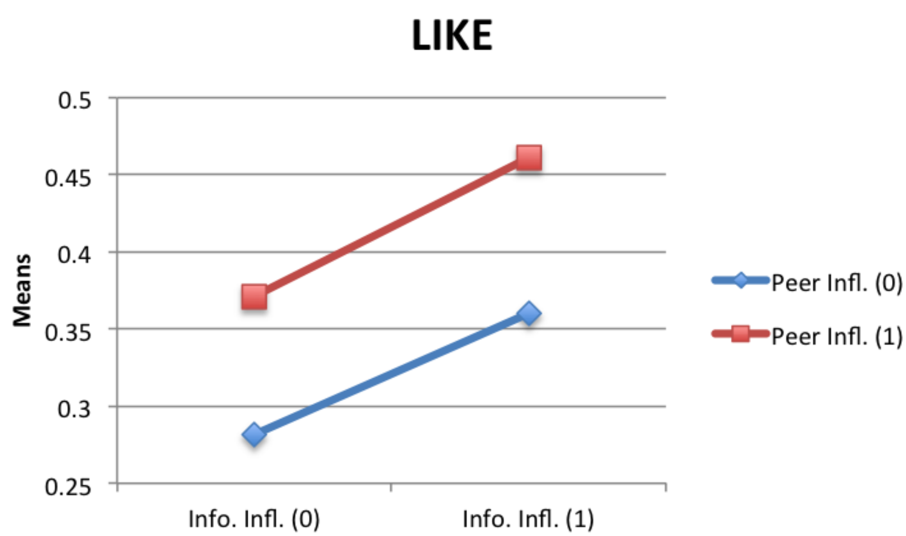


Table 7 reveals the correlation matrix for each of the main variables we have used in this evaluation of the data collected during this round of surveys. We find no indication of multicollinearity.

Table 7. Correlation Matrix

	V1	V2	V3	V4	V5	V6	V7	V8	V9
V1 Peer Inf.	1								
V2 Info. Inf.	0.172	1							
V3 Artist Pop	0.000	0.000	1						
V4 Artist Rock	0.000	0.000	-0.333	1					
V5 Artist Country	0.000	0.000	-0.333	-0.333	1				
V6 Artist Rap	0.000	0.000	-0.333	-0.333	-0.333	1			

V7 Soc. Pres.	0.103	-0.071	0.000	0.000	0.000	0.000	1		
V8 Infl. Suscep.	0.064	-0.112	0.000	0.000	0.000	0.000	0.290	1	
V9 Indie Pref.	-0.187	-0.161	0.000	0.000	0.000	0.000	-0.127	0.010	1
V10 Instrument	-0.065	-0.024	0.000	0.000	0.000	0.000	-0.144	0.041	0.161
V11 Band	-0.101	-0.078	0.000	0.000	0.000	0.000	-0.098	0.003	0.087
V12 Mean. of Like	-0.036	-0.031	0.000	0.000	0.000	0.000	-0.211	-0.177	-0.022
V13 FB Friends	0.028	-0.009	0.000	0.000	0.000	0.000	0.050	0.057	0.005
V14 FB hours	0.003	-0.017	0.000	0.000	0.000	0.000	0.286	0.004	0.016
V15 Age	-0.087	0.210	0.000	0.000	0.000	0.000	0.066	-0.086	-0.053
V16 Gender	0.060	-0.066	0.000	0.000	0.000	0.000	0.016	0.076	0.001
V17 Ethnicity	0.065	0.065	0.000	0.000	0.000	0.000	0.045	-0.014	-0.031
	V10	**V11**	**V12**	**V13**	**V14**	**V15**	**V16**	**V17**	
V10 Instrument	1								
V11 Band	0.503	1							
V12 Mean. of Like	0.091	-0.003	1						
V13 FB Friends	0.016	-0.028	-0.112	1					
V14 FB hours	-0.145	-0.029	0.082	-0.003	1				
V15 Age	-0.060	-0.028	-0.042	-0.174	0.060	1			
V16 Gender	0.082	0.082	-0.086	-0.010	0.010	-0.103	1		
V17 Ethnicity	0.030	0.031	-0.003	-0.160	-0.027	0.103	0.003	1	

We used a generalized estimating equation (GEE) approach to determine levels of support for our hypotheses[1] (Liang and Zeger 1986; Zeger et al. 1988; Zorn 2001). Table 8 presents the results of this GEE analysis in a stepwise fashion, employing the main effects of interest: *Peer Influence* and *Informational Influence* (PI, II, PIxII). We observe significance in the Wald χ^2 from all models (Tables 8 and 9) in our analysis, indicating a progressive and significant fit of our models. Our models were run with the `eform` option, returning odds ratios for the coefficients.

Table 8. Analysis: Main Effects, Interaction

	Dependent Variable: LIKE			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Independent Variable	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**
Peer Influence	1.6961*** (0.3214)		1.5928*** (0.3040)	1.5898* (0.4504)
Info. Influence		1.6140*** (0.3068)	1.5030** (0.2876)	1.5005 (0.3959)
PI * II				1.0035 (0.3837)
ARTIST_POP	4.9309*** (1.0692)	4.9099*** (1.0620)	5.0052*** (1.0965)	5.0052*** (1.0965)
ARTIST_ROCK	1.0000 (0.2279)	1.0000 (0.2274)	1.0000 (0.2297)	1.0000 (0.2297)
ARTIST_COUNTRY	1.5735** (0.3437)	1.5718** (0.3426)	1.5795** (0.3480)	1.5795** (0.5480)
ARTIST_RAP	BASELINE; OMITTED			
Constant	0.2595*** (0.0513)	0.2591*** (0.0525)	0.2145*** (0.0470)	0.2147*** (0.0504)
Wald χ^2	79.91***	79.12***	82.24***	82.25***

[1] We utilized the Stata 12 statistical package and the xtgee command, with options set to evaluate a repeated measures logit regression

	***p < 0.01	**p <0.05	*p < 0.10

As expected, we see individual preference plays a significant role in all models. Of key interest to our study are the positive significant odds ratios returned for our main effects: *Peer* and *Informational Influence*. Models 1 and 2 demonstrate PI and II increasing LIKE by 69.6% and 61.4%, respectively. This holds true, to a slightly lesser degree, in Model 3 lending support for H1 and H2. There is no significant interaction effect (PI x II). Based on this observation, we see no support emerge for H3. However, the continued significance of PI in this observation lends further support for H2.

Table 9. Analysis: Main Effects, Moderators, Interactions

	Dependent Variable: LIKE			
	Model 1	**Model 2**	**Model 3**	**Model 4**
Independent Variable	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**
Peer Influence	1.5877** (0.3060)	1.6986 (1.1288)	1.7137*** (0.3296)	1.0801 (0.7534)
Info. Influence	1.5142** (0.2927)	1.5444** (0.3006)	6.8262*** (4.6869)	8.3053*** (5.9904)
ARTIST_POP	5.0086*** (1.0970)	5.0278*** (1.1049)	5.1453*** (1.1483)	5.1670*** (1.1565)
ARTIST_ROCK	1.0000 (0.2297)	1.0000 (0.2304)	1.0000 (0.2331)	1.0000 (0.2337)
ARTIST_COUNTRY	1.5798** (0.3479)	1.5816** (0.3495)	1.5899** (0.3557)	1.5919** (0.3571)
ARTIST_RAP	BASELINE; OMITTED			
Social Presence	0.9848 (0.0772)	1.0482 (0.1104)	1.2578** (0.1481)	1.2797** (0.1645)
Influence Susceptibility	1.0413 (0.0933)	0.9767 (0.1179)	1.0428 (0.1356)	0.9799 (0.1380)
SP*PI		0.8625 (0.1368)		0.9559 (0.1549)
SP*II			0.6430***	0.6413***

			(0.1021)	(0.1024)
IS*PI		1.1656 (0.2087)		1.2374 (0.2312)
IS*II			1.0148 (0.1799)	0.9519 (0.1780)
Constant	0.2006*** (0.0782)	0.1929*** (0.0969)	0.0787*** (0.0450)	0.0877*** (0.0527)
Wald χ^2	82.40***	83.03***	86.46***	87.19***
		*****p < 0.01**	****p < 0.05**	***p < 0.10**

Table 9 presents the results of our analysis when the moderating factors are introduced into the models. Of interest in this part of the evaluation is the effect of the moderators, *social presence* and *influence susceptibility* (SP and IS). We find no support for H4b and H4d, as neither SP nor IS moderates PI impact. Nor do we see support emerge for H4a as IS does not appear to moderate the effect of II. We find that social presence moderates the impact of Informational Influence on LIKE. This lends support for H4c.

We controlled for misconceptions in the meaning of "LIKE" to examine if the misconceptions confounded the results. However, we found no evidence of confounding effects. It is possible that peer influence interacts with genre preference—in that, when a subject has no priors on quality of music in a particular genre, they may rely on peer and informational indicators. However, when we controlled for genre preference, we did not see significant differences in the main effects of peer and information influence. As mentioned previously, we collected various demographics information from our subjects. Controlling for these demographic variables did not alter the impact of study variables in any significant way.

The final model demonstrates the main effects of peer and informational influence, our repeated measure examining the positive impact of individual preference, and the moderating effect of feelings of social presence on informational influence. Based on these observations of the data, we summarize our findings for this study in Table 10.

Table 10. Summary of Hypotheses and Findings	
Hypothesis	**Results**
H1 Informational Influence drives "Like"	Supported. II had a significant effect on LIKE
H2 Peer Influence drives "Like"	Supported. PI had a significant effect on LIKE
H3 FB Social Influence Interactions	Not supported
H4 FB Moderators	Partially supported. SP was found to have a moderating effect on II (H4c), but no other significant moderating effects were revealed

3.6. Key Findings and Conclusion

The specific aim of this study was to evaluate the effect of differing types of social influencers and the effects that may moderate their overall impact on the decision-making process of Facebook users in regards to digital goods producers. Through our experiment, with a subject base that is representative of the largest single-user base for SMS sites (Brenner 2012), we were able to show how consumers respond to different combinations of positive and negative peer and informational influences while evaluating musicians of differing genres on the Facebook SMS.

We show that personal preference for specific genres of music will continue to drive the choice of musicians on Facebook. Self-reported preference for specific music genres and the decision to “Like” specific artists that fall into that genre were found to be significant across all of our models and studies, including the pilot study, preliminary analysis, and final examination.

In addition to individual preferences, social influence has a significant impact as well. Peer Influence, the conformance to the behavior expected by peers, when presented in a positive manner shows an approximately 70% increase in a student’s decision to “Like” an artist. Informational Influence, the acceptance of opinions of others as reality, increased “Like” by approximately 61%. However, social presence moderates the impact of informational influence.

The lack of support for H3, that an interaction between peer and informational influences exists, is an important takeaway from this analysis. Intuitively one would assume that peer and informational influences, despite being driven by different motivational processes, would complement one another. It is also possible that some users may interpret peer influencers *as* informational influencers, viewing them as simple additional information to contribute to their decision-making process. However, we see no interaction between these two factors emerge in the analysis, indicating that there is no apparent conflation between either of these factors.

It is interesting to observe the impact, or lack thereof, of our moderating factors, social presence and influence susceptibility. In the realm of B2C traditional and e-commerce, research has evaluated and shown both factors to have an effect on consumer decision-making (Bearden et al. 1989; Kumar and Benbasat 2006; Lascu and Zinkhan 1999; Schubert 2000). Our contention has been that the rules change when we shift to *social commerce* and the lack of support that emerged for majority of the moderating effects in our model (H4a,b,d) lends credence to our assertion.

The exception to this is the strong moderating effect that social presence had on the impact of informational influencers (H4c). Social presence is the literal or psychological appearance of one's peers. In traditional e-commerce outlets, this is generated in a largely artificial manner through recommender systems and user forums. Conversely, this speaks to the very core of the *social commerce* experience. As such, it can be expected, and we've demonstrated, that the more one senses the presence of their peers, the less amplified the impact of informational influencers.

There is a lack of support for influence susceptibility as a moderator in our analysis. However, we clearly see an impact of peer influence on the subject's decision-making, which itself conveys social conformity or influence (Bearden and Etzel 1982; Bearden et al. 1989; Park and Lessig 1977). It is possible that influence susceptibility in a general context (as measured by our instrument) is a weaker predictor than a direct measure of peer influence (as manipulated in the experiment). In any case, influence susceptibility manifests in the decision-making process through the significance of peer influence.

One of the key differentiating factors of independent content producers is the lack of the organizational messaging resources reinforcing their product's place in the overall marketplace. Independent producers have to shoulder this burden on their own. In the case of indie musicians, they have to take on the responsibilities that musicians represented by the Big Five can leave to their marketing personnel. The emergence of social media offers a viable platform for independent producers to leverage and reach a broader audience group. This expansion of the engaged base can allow independent content producers to know not only what kinds of messages and content to post and "Like" but they can predict the effect this will have on their followers. Word of mouth (whether through peer or informational means) offers them more understanding on how to effectively reach deeper into the weakly associated networks of "friends" and friends-of-friends on Facebook and leverage the social influences that are built into the Social Media Sites and their respective platforms.

This research has demonstrated positive main effects of informational and peer influences on users' decision to "Like" digital content producers on the Facebook SMS. We have demonstrated that these influencers are a key factor impacting behavior and decision-making on SMS. While we observe impact of social influencers on consumer decision-making, we must still consider the importance of the impact of personal preference, established behaviors, and the informational influencers. This study ultimately raises the discussion into the power of one's peers when the medium changes from direct personal interaction into digital personal interaction, specifically in relation to electronic *social commerce*. Potential future studies can begin to extend these findings to examine these effects on other Social Media Sites with fundamentally different mechanisms, expanding the discussion to include more producer-side measures as well as additional demand-side evaluations, rounding out the discussion so we can more effectively understand the user behavior and unique market attributes present in this growing and evolving medium.

Chapter 4

"OH LORD, PLEASE DON'T LET ME BE MISUNDERSTOOD": MESSAGING AND INFLUENCE EFFECTS ON USER PREFERENCE FOR MUSICIANS ON TWITTER

4.1. Introduction

The Twitter microblogging site, unlike other SMS, is less about expression of relationships and having a centralized hub to socialize with one's friends and more about the rapid dissemination of content and information (Bakshy et al. 2011a; Wu et al. 2011). The key mechanism of the Twitter SMS is the nature of social information dissemination. Much like the Facebook SMS, the effects of Twitter have been evaluated in different social contexts: communication at the workplace (Zhao and Rosson 2009), an outlet for news media (Kwak et al. 2010), and in political campaigns (Wattal et al. 2010; Williams and Gulati 2010). Also like Facebook, research has only begun to evaluate Twitter in terms of *social commerce* and user interaction with content producers. How can these content producers utilize Twitter to drive engagement with consumers, which will hopefully impact sales of their goods and services?

Twitter functions through the mechanism of sending or "tweeting" messages of 140 characters called "tweets" out to the people, or "followers," who subscribe to a user's microblog. These tweets can then, in turn, be forwarded or "retweeted" out to their respective followers. Twitter admins have, in recent updates to the Twitter API, also implemented a function to allow users to "favorite" a message, indicating their approval of the message. "Favoriting" a message doesn't register on a user's Twitter feed, but it does show up on the message itself; the producer can see the number of favorites and if the message is retweeted, the favorites count is sent along with the retweet.

The important differences between Twitter and Facebook allow for an evaluation of the role of different types of social influences as well as the nature of information presented to different users. Twitter is a less experiential site compared to Facebook, featuring less embedded rich media. Twitter requires more active engagement from their users than Facebook, where the interactions are largely passive. However, both of these sites share a similar function: bringing together groups of individuals and organizations and allowing them to engage and interact in a digital context. In the context of *social commerce*, both these sites are the perfect test-bed for evaluating how content producers can effectively leverage the network to drive engagement with consumers of their respective products, which is increasingly difficult in independent, niche markets.

Twitter has been shown to be a strong conduit for electronic word of mouth (eWOM) with research showing that 19% of all microblogs having some mention of a brand with an even split between positive and negative sentiments regarding a product or service (Dwyer 2007; Hennig-Thurau et al. 2004; Jansen et al. 2009). Social contagion and viral/word-of-mouth marketing studies demonstrate that simple broadcasting on social networking platforms, like tweeting or retweeting about a product or service, produces a 246% increase in the rate of adoption of the product/service by the connected members of that person's network, their Twitter followers and their Facebook friends. This demonstrates a clear impact of the social influence effect (Aral and Walker 2011a; Aral and Walker 2011b).

Research has identified two specific types of “content camps” found in messages sent, or tweeted, on Twitter: messages that focus on the self, more personal in nature, known as *meformers*, and messages that are more about the dissemination of informational content, known as *informers* (Java et al. 2007; Naaman et al. 2010). This research gives a foundation by which to evaluate messages and user types on Twitter, but it offers no real robust evaluation of the effect of these messages on user behavior. Additionally, the research has not fully explored the effect of social influences as they may interact with these message types. Nor have we seen these types and influences evaluated as they complement and/or contradict individual user preference for specific types of content and digital goods.

This study contributes to and complements the extant body of research by examining the effect of (a) social influencers and (b) message content type on consumer engagement with digital content producers on the Twitter SMS. We explore the role of interactions between individual preference and specific message types as well as the interactions between personal characteristics, those from Chapter 3 (*social presence* and *influence susceptibility*) as well as different types of self-reported *social media user types*. Of interest are the impact of these effects on not only a user’s desire to “follow” a musician on Twitter, but also their specific interest in engaging with the musician. This is captured in their reported interest in retweeting content and messages sent out by independent digital musicians.

4.2. Perspective and Research Questions

Unlike many SMS, Twitter is an active user engagement experience. While on Facebook, users generally do not actively broadcast their activity, the Facebook SMS will take care of that for them; passively posting comments and behavior on their timeline, which disperses out among their connected network of friends, and even out to friends of friends, leveraging weakly tied entities. Twitter requires users to engage. Messages, or tweets, do not go out without the specific engagement of the user. The social mechanism has the potential to reduce the distance between the three main players: the creator, the sharer, and the sharer's connected network (Bakshy et al. 2011b; Blau 1964; Cook and Emerson 1978; Huberman et al. 2008). In relation to *social commerce*, this active engagement speaks to the heart of the WOM experience on SMS sites (Liu 2006; Mahajan et al. 1984; Tang et al. 2012; Van den Bulte and Lilien 2001).

Facebook is more experiential than Twitter, which offers less rich media and a more minimalistic design. The focus on Twitter is more on the messaging. The lean media approach may arguably be instrumental to Twitter's popularity. Media richness theory refers to properties of communication mediums and how able they are to convey meaning, relevance, and information to a specific audience (Daft and Lengel 1984; Markus 1994). Traditionally, it is the amount of social, non-verbal cues that can be extracted from a particular outlet determines the level of richness of the media involved. For example, face-to-face communication is considered the richest form of communication while a text-based message (email, SMS, etc.) would be considered the leanest messages (Markus 1994). Recent studies have shown that traditional media richness may be slightly different for consumer satisfaction and attitude in the context of websites involving complex vs. simple products (Simon and Peppas 2004). Leaner media may be the preference when the product or service is less complex; for example, a song is far less complex of a product than an automobile (Simon and Peppas 2004). This is consistent with previous studies that examined new media forms of communication as they emerged in the mid-to-late 1990s (Carlson and Zmud 1999; Dennis and Kinney 1998).

Social media site consumers are ultimately seeking to engage in a personal connection to their peers, even if it is only in a psychological sense. The levels to which a person experiences this connection to their peers is often referred to as *social presence* (Fulk et al. 1987; Short et al. 1976). From the relationships and associations with other people on these SMS, users accrue *social capital* (Coleman 1988). The power and versatility of these resources is largely determined by the strength of the ties between people and the density of the network of people (Ellison et al. 2007; Paxton 1999). The Internet and social media platforms enhance the generation of social capital in relationships via the formation and cultivation of weak ties (Resnick 2001). These platforms also have the effect of strengthening social capital gains through the creation of vast networks of weak ties (Donath and Boyd 2004). For example, a study by Intersperience states that the average 22 year old in the UK has over 1,000 Facebook "friends" (Intersperience 2011).

Taking all of this into consideration, the nature of the messages sent by content producers may have a profound impact on these different types of Social Media Site users. Research has identified different message types that can be placed into one of two categories: *meformers*, messages that have a more personal context, contrasted with *informers*, messages that are almost exclusively related to dissemination of actionable information (Naaman et al. 2010).

Given the needs of different users of SMS and the potential that effective simple messaging can have on them, questions arise as to how digital content producers can effectively target their messaging on SMS to better reach these different user types and leverage their social capital to more deeply penetrate their network of strong and weak ties. We ultimately seek to examine messaging and social influencers and their potential interactions on Twitter. In order to properly address this, we aim to answer the following research questions: (1) Does message content type on SMS influence user choice? (2) How do messaging efforts interact with peer and informational influence? And (3) do influence susceptibility, social presence, and SMS user type moderate these main effects? We will utilize the findings and knowledge from the study in Chapter 3, which examined positive and negative social influences, to evaluate the interactions with producer SMS strategies studied in this Chapter.

4.3. Hypotheses and Research Model

Messaging regarding a product and/or brand can encourage consumer confidence in a number of ways. It can provide a guarantee to the customer, both implicitly and explicitly. It can effectively communicate to a consumer the consequences, both positive and negative, that come from adoption. These consequences can be overt, things the product can actually, directly do for the consumer, as well as subtle, serving as a status symbol or communicating power or engendering social approval among peers (Aaker and Keller 1990; Aaker 1997; Sadeghi and Tabrizi 2011)

A breakdown of the types of messages posted to Facebook walls and Twitter feeds has identified several categories of messages, ultimately showing two types of poster, generally driven by need for attention/peer approval (Naaman et al. 2010; Rui and

Whinston 2011): *informers*, those who post messages of strong informational content (ex. "The concert tonight is located at ___ at ___pm"), and *meformers*, those who generally post conversational messages, mostly about themselves (ex. "I had a great time at the concert last night") (Naaman et al., 2010). These Tweet Types coincide with the types of people looking for these specific types of messages, people seeking specific, actionable *information* and those looking for a more generic *social* experience, respectively (Java et al. 2007; Shi et al. 2011). Empirical studies of Twitter archives have found that 80% of users fit the *meformer* messaging profile; yet *informers* had far more friends/followers (median=131) than *meformers* (median=42) (Ehrlich and Shami 2010; Kıcıman 2010; Naaman et al. 2010). That *informers* seem to drive connections more than *meformers* is in contrast to behavioral research the shows consumption behavior is driven by the need for people to enhance their self-concept and standing with others. This is often achieved through personal connections with brands, products, and content producers (Belk 1988; Escalas and Bettman 2005; Richins 1994). This drive to connect parallels the sentiments reflected in personal relations often felt to celebrities and musicians by users of SMS, as well as those of the students originally involved in the discussion that launched this research (Donath and Boyd 2004).

Given these implied relationships that emerge from connections SMS users make with content producers on SMS, we intend to measure the effect that Tweet-type (*meformer* vs. *informer*), has on the decision-making process of music consumers on the Twitter SMS.

H1 (Tweet Type Profile-Level Hypothesis)

a. **Musician Tweet Type will impact a user's decision to "follow"**

b. **Musician Tweet Type will impact a user's decision to "retweet" messages**

Social influence has been operationalized as expressions of *informational* influences as a person's willingness to accept the views of others as a definition of reality (Deutsch and Gerard 1955) and expressions of *normative* influences in the form of behavior adopted based on how other's may perceive actions we take (Bearden et al. 1989; Moschis and Churchill Jr 1978; Park and Lessig 1977). We closely examined the effect of social influence on the experiential and more passively driven Facebook SMS in the study presented in Chapter 3. We found that *social influencers*, represented as both *informational* and *peer influence*, both had a positive main effect on user decision-making for indie musicians on Facebook. Engagement is different on Twitter as opposed to Facebook: there is a more active dissemination of information. However, users are still acting in an open, public forum that can be viewed and judged by their network of peers.

Given that we are evaluating the informational content of tweets sent out from the producers themselves, we study the effect of influencers in terms of the overall construct of *social influence*, representing mostly positive and negative peer influencers. Of specific interest in this study is the power of these social influencers on this leaner, more actively engaging SMS.

H2 (Twitter Influence Hypothesis)

a. **Social Influence will impact a user's decision to "follow" a musician on Twitter**

b. **Social Influence will impact a user's decision to "retweet" messages from a musician on Twitter**

The implication of social influencers is the adjustment of behavior in the presence of the pressure from one's peers. Given the highly connected nature of SMS, it makes sense that acceptance or denial of messages based on their content would be impacted by the presence of these social influencers. Our evaluation thus far is based on the content of messages sent and the language employed, and the expected conformity to societal norms on SMS. At the intersection of these two theory bases is an expression of Language Expectancy Theory (LET); a persuasion theory which determines behavior based on a series of expectations of behavior expressed in messages from the initial communicator in conjunction with the individual's expected societal norms (Burgoon et al. 2002; Burgoon and Miller 1985; Cameron et al. 2012).

LET states that messengers with lower status or perceived credibility, based partially on the lack of power they hold in society, have less freedom in the types of messages they can communicate; based on this limited messaging freedom, these low power/status individuals generally have to conform greater to societal expectations (Burgoon et al. 2002; Burgoon and Miller 1985). In our specific context, indie musicians lack the same credibility and status of musicians represented by the Big Five and may need to conform in a greater way to expectations of behavior and message content on Twitter. The impact of the persuasive nature of the tweets sent by producers stands to be enhanced or augmented in our context when the societal norms are not necessarily dictated by the users themselves but rather by the extended network of the users' peers (Bearden et al. 1989; Triandis 1980). This is observed by an active acceptance of a content producer and/or the decision to retweet messages. Given this, we will evaluate the interaction effects of producer Tweet Type and social influence.

H3 (Twitter Interactions Hypothesis)

a. **Tweet Type and Social Influence together will impact a user's decision to "follow" a musician on Twitter**
b. **Tweet Type and Social Influence together will impact a user's decision to "retweet" messages from a musician on Twitter**

SMS are intensely personal, offering an opportunity to give a direct connection between individuals and organizations. Given the personal nature of these relationships, we have to give credence to the impact of influence observed when a person conforms to the perceived behavioral norms of their immediate and weakly-connected social networks (Bearden and Etzel 1982; Park and Lessig 1977). This impact of utilitarian social influence implies an adjustment of behavior to avoid punishment and/or achieve personal gratification (Asch 1952; Festinger 1953; Lascu and Zinkhan 1999). As stated in chapter 4, this is *a priori* behavior, which generally manifests itself in the form of an individual's *susceptibility* to interpersonal influence.

It makes intuitive sense that the more susceptible a user is to social influences and the potential judgment of others, the more they will alter their behavior on SMS. Specifically in regard to Twitter, they may choose not to follow specific users or companies. Or they may ultimately choose to follow, but not actively engage with, users or companies by not retweeting messages they send out. Using Bearden et al's (1989) self-reporting measures, we determine an individual's *influence susceptibility* in regards to their engagement with digital content producers in the presence of pressure from their peers on Twitter.

H4 (Twitter Influence Susceptibility Hypothesis)

a. **Influence Susceptibility will moderate the effect of Tweet Type on the user's decisions on Twitter**
b. **Influence Susceptibility will moderate the effect of Social Influences on the user's decisions on Twitter**

The extent to which a SMS, or any other communication medium, allows users to create or observe a personal connection with their fellow users is generally referred to as *social presence* (Short et al. 1976). The implication of social presence in regards to SMS is that one's peers appear to be present, even if only in a virtual sense (Fulk et al. 1987). Sites and portals on the Internet can often feel somewhat impersonal as there is an inherent, albeit false, sense of anonymity. Because of this sterile environment, social presence has become an important metric, as it augments the experience that users have with others (Kumar and Benbasat 2006; Schubert 2000).

We did not find any moderating effect of social presence in the Facebook study (chapter 4), however this may lie in the nature of engagement on that particular SMS. Most of the research surrounding the phenomenon of social presence in the context of e-commerce and electronic communications has evaluated this effect in an active manner: you are engaging with your peers on a site or portal with the full knowledge of your peers being present (Karahanna and Straub 1999; Kumar and Benbasat 2006; Zhu et al. 2010). In terms of Twitter, which requires this type of active engagement, this may allow for a stronger sense that your peers are experiencing the moment with you in a more real-time fashion (Cheung et al. 2011; Kaplan and Haenlein 2010). This stands in direct contrast to the asynchronous nature of engagement on Facebook, which may not be conducive to create an active environment required for the social presence effect.

If a user feels a stronger presence of their peers and producers engaging with them in the moment, it stands to reason that this social presence will have an effect on the way in which they engage in return. Using the established measures employed in chapter 4 (Karahanna and Straub 1999; Kumar and Benbasat 2006; Short et al. 1976), we will evaluate the impact of social presence on the main effects of Tweet Types from the producers and influence from peers.

H5 (Twitter Social Presence Hypothesis)

a. **Social Presence will moderate the effect of Tweet Type on the user's decisions on Twitter**
b. **Social Presence will moderate the effect of Social Influences on the user's decisions on Twitter**

Research has identified four reasons that people engage with Social Media Sites: 1) socializing, 2) entertainment, 3) self-status seeking (social contagion), and 4) information seeking (Java et al. 2007; Park et al. 2009). Those seeking a *social* experience on a network such as Facebook are mostly interested in conversations (wall, twitter feed, status updates) and engendering a sense of community; seeking peer approval and support was found to be a peripheral driver for *socializers*. Those seeking *entertainment* on social networks find groups and pages specifically focused on a person or product with high leisure value (movies, music, games, etc.). Those interested in *status* or having a high profile generally utilize groups and pages simply to drive social approval of their peers, they typically have abnormally high numbers of friends and are easily driven by the pressure from their peers to participate in groups, "follow" certain people on Twitter, or "Like" pages on Facebook. *Information seekers* generally gravitate toward pages that contain details about social and professional events, as well as details regarding goods and services, including editorial opinions for product categories (ex. gamer blogs, music reviews, etc.) (Moore and McElroy 2011; Park et al. 2009; Pempek et al. 2009).

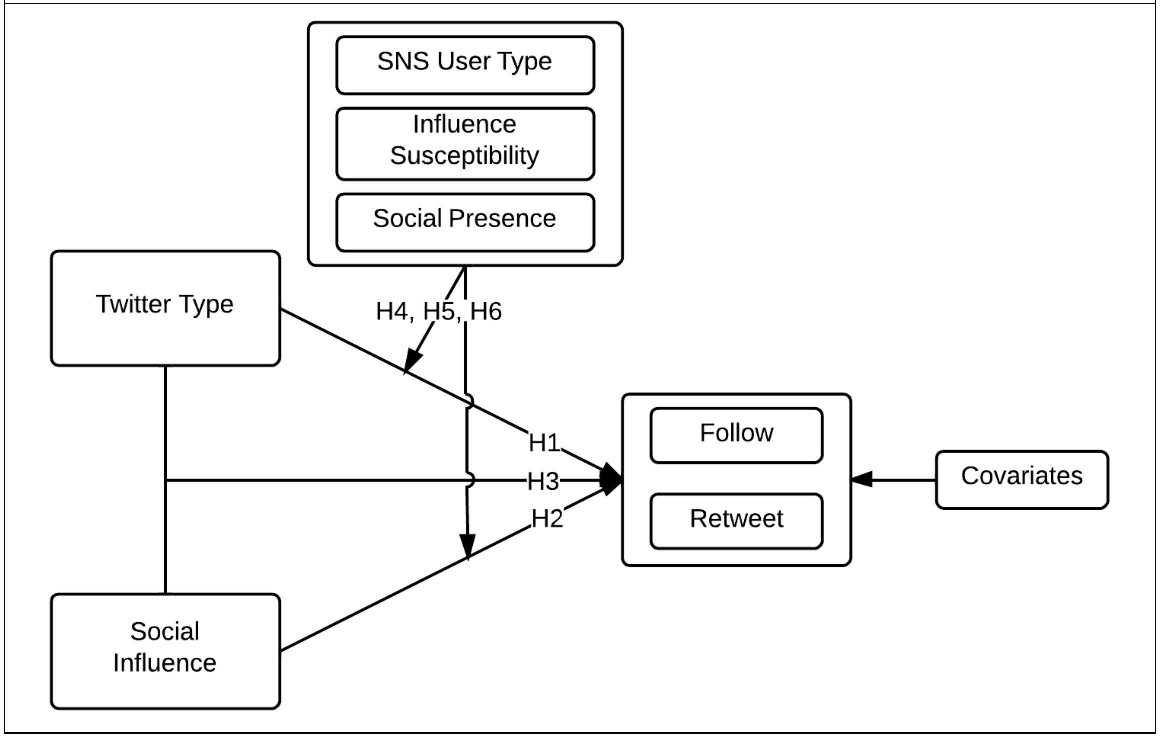
Given the alignment between the goals of these different types of social media users and (a) the nature of each Tweet Type and (b) the evaluated impact of social influencers, we will examine the effect that different SMS user types have on user decision-making toward indie musicians on Twitter.

H6 (Twitter SMS User Type Hypothesis)

a. **Social Media User Type will moderate the effect of Tweet Type on the user's decisions on Twitter**
b. **Social Media User Type will moderate the effect of Social Influences on the user's decisions on Twitter**

Figure 3 summarizes the hypothesized relations and presents the complete research model for this study.

Figure 3. Research Model



4.4. Study Design

The experiment, presented in Table 11, uses a 2 x 3 mixed design on the factors of *Influence* and *Twitter Type*. This first factor is varied on two levels, *negative influence* (INF = 0), *positive influence* (INF = 1). The second factor is also varied on similar levels, *meformer tweets* (TT = 0), *informer tweets* (TT = 1), and *combination me/informer tweets* (TT = 2). Four repeated measures of each DV, "Follow" as well "Likelihood to Retweet," were gathered for each subject as explained below.

Table 11. 2x3 Experiment Design

	Tweet Type		
	[A] Meformer (TT = 0)	[B] Informer (TT = 1)	[C] Mixed (TT = 2)

Influence	Negative Influence (INF = 0)	Negative Influence (INF = 0)	Negative Influence (INF = 0)
	[D] Meformer (TT = 0) Positive Influence (INF = 1)	[E] Informer (TT = 1) Positive Influence (INF = 1)	[F] Mixed (TT = 2) Positive Influence (INF = 1)

For this study, we evaluated each of the six treatment groups using a representative sample of undergraduate students in Arizona State University. The context of the experiment and what was expected of them was explained to the participant(s), after which they answered questions to determine (a) their preference across our four genres of interest—rock, pop, country, and rap (Pachet and Cazaly 2000; Rentfrow and Gosling 2003), (b) their self-reported Twitter usage, and (c) basic demographic information. They were then shown the main Twitter pages for each of the four artists, samples of tweets sent by these artists varied across the different types of tweets (*meformer/informer*), media samples from the artists (to control for and avoid the potential confounding effect of genre preference), and messages from other undergraduate students, represented as tweets, regarding their opinions of the artist in each of the experiment settings, holding TT and INF constant across each artist for each subject. These tweets from fellow undergraduate students were either positive or negative opinions, serving as the manipulation for social influence.

After showing each page and experiencing the sample music, respondents were asked whether they would choose to "follow" the particular artist, as well as a series of questions to determine their "intention to retweet" messages from this artist to their followers. Each respondent also was asked to fill in two questions, serving as manipulation checks—"One of the Tweets I saw for this artist was…"—from a selection of peer comments from each of the varying levels of influence, only one of which would be correct for their response group. The process was repeated for the remaining artists. Finally, they were presented with a series of questions on a seven-point Likert scale to measure *social media user type*, *influence susceptibility,* and *social presence*.

4.4.1. Twitter

Subjects were shown a series of Tweets that originate from one of the four musicians of interest. These tweets were categorized as one of the two types identified (*meformer/informer*) or some combination thereof, depending on the treatment group to which they belonged. While they were evaluating these messages, they were also listening to a sample of music from that particular artist. Depending on their treatment group, subjects received either a positive or negative social influencer in the form of tweets from other students. Each tweet had two "hashtags" associated with it, one naming the artist in question (eg. #gangstagrass) and the second representing their "decision" to follow this artist on Twitter; #yes for positive social influence, #no for negative social influence. Once this was completed, subjects addressed additional questions related to the dependent variables for this study: whether they choose to "follow" this musician on Twitter and a brief explanation why as well as a series of questions derived from Oliver and Swan's (1989) interpretation of the *Customer Satisfaction Scale* and Zeithaml et al's (1996) *Loyalty Intent Scale* (Arens and Rust 2012; Oliver and Swan 1989; Zeithaml et al. 1996) to evaluate their *intent to retweet* messages from this artist, being the second DV of interest in our study. Additional demographic information (age, gender, race, and involvement in music) were also gathered.

4.4.2. SMS User Type, Social Influence, and Social Presence

For the purposes of this study, it is necessary for us to gauge the type of user that may be participating in our study. Given the wild popularity of Twitter, we are making the assumption that university-age students will be active participants. Our assertion is that different user types will respond to message types in a slightly different manner from each, based on each group's needs, hence the hypothesized moderating effect. Using measures from Park et al. (2009), which were adapted from Lin (2006) and Ridings and Gefen's (2004) constructs for evaluating participation in and attraction to virtual communities.

For evaluating their susceptibility toward social influencers, we use measures adapted from Park and Lessig (1977) and Bearden et al. (1989). They adhere to established levels of influences—informational and normative—but allow the user to self-report, giving us a general context for their leanings in this area. These measures have been adjusted to reflect the Twitter SMS. For *social presence*, we employ Kumar and Benbasat's (2006) construct recontextualized for Twitter (Karahanna and Straub 1999; Kumar and Benbasat 2006; Short et al. 1976).

The measures discussed in this section are presented in Appendix D. A sample of positive and negative peer tweets as well as a sample of *meformer* and *informer* artist tweets can be found in Appendix E.

4.5. Results and Analysis

This section begins with a brief discussion of the descriptive statistics for the sample population, an examination of the subject's understanding of the meaning of "follow" on Twitter, and a review of the correlation matrix for this study. We then present a discussion for both dependent variables of interest for our group of independent musicians, *desire to follow* and *intention to retweet*. The results and analysis for each DV is presented in the following manner: (1) initial evaluation of the marginal means by artist, (2) examination of the main effects of Tweet Type, Influence, and the interaction (TT x INF) on our DV, and (3) an evaluation of the moderating effects in each model. After presenting all of the results for both DVs, we offer a discussion and interpretation of the findings.

4.5.1. Descriptive Statistics

A total of 684 respondents participated in this experiment. From these samples, we obtained 335 usable and completed surveys. Survey responses were discarded for (1) respondents who self-reported as being under the age of eighteen, (2) subjects reporting zero or null for number of users followed on Twitter, this being the indicator that they do not actually use the Twitter SMS, (3) subjects who responded true to the final statement regarding messaging on Twitter, as reported in Table 13, (4) students who did not fill in responses to the manipulation check questions, and (5) students who demonstrated a lack of interest in responding to the survey questions—e.g. reporting all 1s or 7s for every sample construct. The largest group of samples dropped were due to users indicating they do not use the Twitter SMS, as indicated by responding with zero or null for number of users followed; the remaining descriptive measures for Twitter usage are of interest, but do not indicate that users do or do not use the Twitter SMS—e.g. some Twitter users follow other users, but do not have followers themselves nor do they send tweets, as such, these users clearly utilize the service, but may have different goals in doing so. Descriptive statistics from the final sample in this experiment are shown in Table 12.

<table>
<tr><th colspan="6">Table 12. Descriptive Statistics</th></tr>
<tr><td>N</td><td colspan="5">335 [A] 84 [B] 54 [C] 32 [D] 92 [E] 50 [F] 23</td></tr>
<tr><td>Age</td><td colspan="5">18: 196 (59%)
19: 85 (25%)
20-21: 38 (11%)
>21: 16 (5%)

Min: 18 Max: 39 Mean: 18.89</td></tr>
<tr><td>Gender</td><td colspan="5">Male: 169 (50%)
Female: 166 (50%)</td></tr>
<tr><td>Ethnicity</td><td colspan="5">Caucasian (=0): 201 (60%)
African-American (=1): 15 (4%)
Hispanic (=2): 52 (15%)
Indian (=3): 1 (1%)
Asian (=4): 36 (11%)
Native American (=5): 11 (3%)
Other (=6) 19 (6%)</td></tr>
<tr><td># of Users Followed</td><td colspan="5">Min: 0 Max: 1026 Mean: 125.64 Median: 100</td></tr>
<tr><td># of Followers</td><td colspan="5">Min: 0 Max: 1000 Mean: 122.78 Median: 81</td></tr>
<tr><td># of Twitter Hours (day)</td><td colspan="5">Min: 0.1 Max: 75 Mean: 1.61 Median: 1</td></tr>
<tr><td># of Tweets Sent (day)</td><td colspan="5">Min: 0 Max: 200 Mean: 4.88 Median: 1</td></tr>
<tr><td># of Retweets (day)</td><td colspan="5">Min: 0 Max: 31 Mean: 2.85 Median: 1</td></tr>
<tr><td># of Musicians Following</td><td colspan="5">Min: 0 Max: 200 Mean: 9.76 Median: 2</td></tr>
<tr><td>Indie Preference</td><td colspan="5">Min: 1 Max: 4 Mean: 2.56</td></tr>
<tr><td>Play an Instrument?</td><td colspan="5">Yes: 201 (60%)
No: 134 (40%)</td></tr>
<tr><td>Been in a Band?</td><td colspan="5">Yes: 132 (40%)
No: 203 (60%)</td></tr>
<tr><td rowspan="5">Genre Preferences</td><td></td><td>1 (highest)</td><td>2</td><td>3</td><td>4 (lowest)</td></tr>
<tr><td>Rock (1):</td><td>117</td><td>64</td><td>72</td><td>82</td></tr>
<tr><td>Pop (2):</td><td>97</td><td>106</td><td>84</td><td>48</td></tr>
<tr><td>Rap/Hip-Hop (3):</td><td>135</td><td>71</td><td>77</td><td>52</td></tr>
<tr><td>Country (4):</td><td>83</td><td>60</td><td>62</td><td>130</td></tr>
</table>

Once again, we find the distribution of ages is in accordance with expectations for the study population with the majority of respondents being aged 18 or 19. The distribution of gender is much more evenly distributed in this sample, which should offer a better examination of gender as a factor in Twitter usage. However, as in Chapter 3, the population of respondents is disproportionately Caucasian. While we collected preferences for various genres, the genres of interest were aligned with the four artists sampled (POP, ROCK, COUNTRY, RAP) as well as their reported preference for Independent artists compared to "superstar" artists—those represented by one of the Big Five record labels (INDIE).

Table 13. "Follow" Check Questions

	Statement	True		False	
1	**My decision to Follow gets registered on the person/company's Twitter page**	162	48%	173	52%
2	**My decision to Follow gets posted on my Twitter feed**	90	27%	245	73%
3	**By default, my decision to Follow gets posted on my followers' Twitter feed(s)**	73	22%	262	78%
4	**I get Tweets on my Twitter feed from that person/company**	252	75%	83	25%
5	**By default, my decision to Follow gets posted on the Twitter feed of followers of my followers**	36	11%	299	89%
6	**I get money from the person/company I chose to Follow**	4	1%	331	99%

Table 13 shows the results from the respondents' self-reported thoughts regarding the effect of choosing to Follow users on Twitter. The difference between Twitter and Facebook becomes clearer here. With Facebook, information is disseminated passively and generally without participation and even knowledge of the user. On the other hand, with Twitter users have to actively present information or actively seek information regarding their followers or those they choose to follow. To this end, to better ensure the validity of our results, we collected information regarding their beliefs surrounding the potential impact of their decision to "Follow" someone on Twitter. With Facebook, the majority of correct responses were "true" while with Twitter, majority of correct responses is "false." Once again, statement 6 is absurd and used as a check for validity of responses. An observation here is that the larger number of accurate responses indicate that more users understand the mechanics of Twitter than the demonstrated understanding of Facebook by respondents in Chapter 3.

Table 14. Correlation Matrix

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
V1 Twitter Type	1									
V2 Influence	-0.075	1								
V3 Artist Pop	-0.067	0.233	1							
V4 Artist Rock	0.016	0.169	0.209	1						
V5 Artist Country	0.038	0.130	0.079	0.230	1					
V6 Artist Rap	-0.027	0.107	0.197	0.143	0.152	1				
V7 Infl. Suscep.	-0.007	0.069	-0.004	0.076	0.093	0.179	1			
V8 Soc. Pres.	0.043	0.060	-0.068	0.014	0.081	0.065	0.400	1		
V9 SMS Type	0.033	0.068	0.047	0.094	0.128	0.178	0.538	0.490	1	
V10 Instrumen t	-0.085	0.049	0.070	0.043	0.026	0.003	-0.022	-0.022	0.040	1
V11 Band	-0.133	-0.012	0.081	-0.005	-0.030	0.004	-0.032	-0.015	0.045	0.509
V12 Indie Pref.	0.054	0.031	0.277	0.059	-0.057	-0.009	-0.049	-0.064	0.010	0.084
V13 No. Following	-0.052	0.031	0.016	-0.053	-0.027	0.059	0.055	0.231	0.178	-0.078

V14 No. Followers	-0.028	0.038	-0.128	-0.076	-0.047	-0.023	-0.017	0.257	0.121	-0.075
V15 Twitter Hours	0.133	-0.107	-0.057	-0.056	-0.052	-0.013	0.130	0.092	0.079	-0.035
V16 Tweets Sent	0.010	-0.053	-0.063	-0.075	-0.118	-0.088	0.088	0.130	0.108	-0.028
V17 Tweets RT	0.079	-0.061	-0.115	-0.036	0.002	0.019	0.153	0.232	0.160	-0.024
V18 Gender	-0.024	0.086	0.152	0.053	0.126	-0.009	-0.108	0.010	0.012	-0.020
V19 Age	0.012	0.098	0.020	0.127	0.009	-0.016	0.000	-0.067	-0.073	0.114
V20 Ethnicity	0.064	-0.013	0.057	-0.005	0.069	0.051	0.019	0.077	0.204	0.145
	V11	**V12**	**V13**	**V14**	**V15**	**V16**	**V17**	**V18**	**V19**	**V20**
V11 Band	1									
V12 Indie Pref.	0.108	1								
V13 No. Following	0.010	-0.026	1							
V14 No. Followers	-0.036	-0.071	0.581	1						
V15 Twitter Hours	-0.086	0.007	0.085	0.111	1					
V16 Tweets Sent	0.010	-0.012	0.164	0.374	0.157	1				
V17 Tweets RT	-0.022	-0.103	0.276	0.382	0.338	0.536	1			
V18 Gender	-0.066	0.003	0.069	0.061	-0.003	0.014	0.112	1		
V19 Age	0.040	0.087	-0.012	-0.092	0.138	-0.053	-0.011	-0.022	1	
V20 Ethnicity	0.054	-0.050	-0.003	0.065	0.136	0.114	0.157	0.030	0.207	1

Table 14 presents the correlation matrix for the main variables of interest and controls used in the evaluation of the data collected in these surveys. There is no indication of multicollinearity.

In the following two sections, the data are examined in regards to the two DVs of interest in this study, whether or not a subject would follow the musician on Twitter (FOLLOW) and their intention to retweet messages from that musician (RETWEET).

4.5.2. Follow

Main Effects

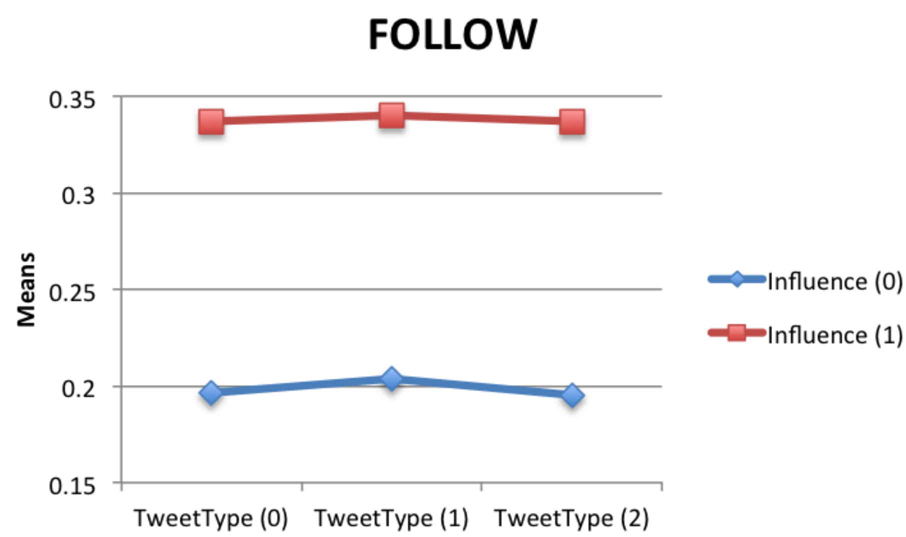
Table 15 presents the marginal means for each treatment across all four artists of interest, representing the within-subject factor (ARTIST_POP, ARTIST _ROCK, ARTIST _COUNTRY, ARTIST _RAP). The marginal means for the DV (FOLLOW) are presented in Table 15 as well. The cell means for FOLLOW are aggregated and presented graphically in Figure 4. From the means and the F-tests reported in Table 15 and Figure 4, there is initial evidence that influence has a significant effect on FOLLOW for each artist, providing support for H2a. However, the F-tests and means do not appear to show significance for Tweet Type on FOLLOW for any of the artists, indicating an initial lack of support for H1a. Nor do we see any apparent interactions between Tweet Type and Social Influence impacting FOLLOW (Figure 4), leading to a potential lack of support for H3a.

Table 15. Marginal Means of the Effect of TT and INF on FOLLOW

ARTIST_POP				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	0.3466	0.3558	0.2364	**1.35**
	Negative	**Positive**		**F**
Influence (INF)	0.2235	0.4424		**19.03*** **
ARTIST_ROCK				

	Meformer	Informer	Mixed	F
Tweet Type (TT)	0.1477	0.1923	0.1455	**0.54**
	Negative	**Positive**		**F**
Influence (INF)	0.1000	0.2242		**9.78*** **
ARTIST_COUNTRY				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	0.3295	0.3462	0.3818	**0.25**
	Negative	**Positive**		**F**
Influence (INF)	0.2824	0.4061		**5.75** **
ARTIST_RAP				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	0.2557	0.1827	0.2545	**1.06***
	Negative	**Positive**		**F**
Influence (INF)	0.1798	0.3191		**3.87** **
FOLLOW (Total)				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	0.2699	0.2692	0.2545	**0.11**
	Negative	**Positive**		**F**
Influence (INF)	0.1985	0.3379		**34.01*** **
				***** p < 0.01 ** p < 0.05 * p < 0.10**

Figure 4. Effect of TT and INF on FOLLOW for All Artists



Similar to the analysis in Chapter 3, we used a generalized estimating equation (GEE) approach to evaluate the support for this study's hypotheses[2] (Liang and Zeger 1986; Zeger et al. 1988; Zorn 2001). The models in this analysis were run with the `eform` option, so the coefficients reported here are odds ratios. Table 16 reports the results of the GEE in a stepwise manner, utilizing the main effects of interest: *Tweet Type* (TT), *Influence* (INF), and the interaction effect (TTxINF). For our analysis, we have broken down Tweet Type into the respective types, *Meformer*, *Informer*, and Mixed. The effects of *Meformer* and *Informer* are reported relative to that of Mixed. Based on the significant Wald χ^2 from all the models in this DV's analysis (Tables 16 and 17), there is an indication of a progressive and significant fit for all of the models evaluating the effect on FOLLOW.

[2] We utilized the Stata 12 statistical package and the xtgee command, with options set to evaluate a repeated measures logit regression

Table 16. Analysis: Main Effects, Interaction on FOLLOW				
Dependent Variable: FOLLOW				
	Model 1	Model 2	Model 3	Model 4
Independent Variable	Exp(b) (Std. Error)	Exp(b) (Std. Error)	Exp(b) (Std. Error)	Exp(b) (Std. Error)
TT_Meformer	1.0886 (0.2378)		1.0074 (0.2192)	1.0088 (0.3191)
TT_Informer	1.0079 (0.1855)		1.0342 (0.2421)	1.0635 (0.3592)
Influence		2.0998*** (0.3229)	2.1000*** (0.3237)	2.1412** (0.8152)
TT_Meformer * INF				0.9944 (0.4340)
TT_Informer * INF				0.9491 (0.4448)
ARTIST_POP	1.6329*** (0.2591)	1.6550*** (0.2693)	1.6550*** (0.2694)	1.6550*** (0.2694)
ARTIST_ROCK	0.6331** (0.1139)	0.6271** (0.1153)	0.6271** (0.1153)	0.6271** (0.1154)
ARTIST_COUNTRY	1.7225*** (0.2723)	1.7487*** (0.2835)	1.7487*** (0.2836)	1.7487*** (0.2836)
ARTIST_RAP	BASELINE; OMITTED			
Constant	0.2833*** (0.0618)	0.2031*** (0.0323)	0.2001*** (0.0465)	0.1982*** (0.0576)
Wald χ^2	44.20***	64.26***	64.29***	64.30***
	***p < 0.01		**p < 0.05	*p < 0.10

Once again, individual preference clearly plays a significant role in all of the models. But the key interest of this study is the positive significant odds ratios returned for the main effect of Social Influence. Model 2 demonstrates Influence increasing FOLLOW by 109.98% with Models 3 and 4 demonstrating comparable levels of the effect of Influence lending strong support for H2a. However, there is no demonstrated impact of either Tweet Type, offering no support for H1a at this point. Nor do we see any significant interaction effect (TT x INF), lending no support for H3a. However, the continued significance of Influence in the presence of the interaction gives further support to H2a.

Interactions and Moderators

Much like the study in Chapter 3, we controlled for misconceptions in the meaning of FOLLOW to examine if the misconceptions confounded the results. However, we found no evidence of confounding effects. Once again, it is possible that Influence interacts with genre preference– in that, when a subject has no historical context on the quality of music in a particular genre, they may rely on social indicators. However, as in Chapter 3, when we controlled for genre preference, we did not see significant differences in the main effect of Social Influence. Though we did find a significant interaction between the Informer Tweet Type and individual genre preference, we explore this in the results presented in Table 17 and the subsequent discussion. We also found significant effects in some of the demographics and covariates, so these factors were included in this study's analysis.

Table 17. Analysis: Main Effects, Moderators, Interactions on FOLLOW

Dependent Variable: FOLLOW				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Independent Variable	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**
TT_Meformer	1.0567 (0.2275)	1.5149 (0.9519)	1.0972 (0.6708)	0.6526 (0.4701)
TT_Informer	0.6941 (0.2396)	0.3717 (0.2688)	0.3227 (0.2319)	0.0965*** (0.0836)
Influence	1.9826*** (0.3026)	1.1728 (0.4749)	1.0519 (0.4630)	0.4383 (0.2347)
ARTIST_POP	1.4065*	1.3994*	1.4026*	1.4064*

	(0.2837)	(0.2791)	(0.2816)	(0.2864)
ARTIST_ROCK	0.4836*** (0.1123)	0.4881*** (0.1122)	0.4857*** (0.1124)	0.4835*** (0.1133)
ARTIST_COUNTRY	1.5630** (0.3132)	1.5527** (0.3075)	1.5573** (0.3105)	1.5628** (0.3160)
ARTIST_RAP	BASELINE; OMITTED			
TT_Informer*POP	1.8617* (0.6998)	1.8896* (0.7102)	1.8832* (0.7105)	1.9537* (0.7565)
TT_Informer*ROCK	2.2095** (0.9161)	2.1908** (0.9074)	2.2010** (0.9151)	2.2168* (0.9435)
TT_Informer*RAP	1.6009 (0.6015)	1.6267 (0.6111)	1.6201 (0.6109)	1.6759 (0.6485)
Social Presence	0.9738 (0.0612)	0.9948 (0.1575)		
Influence Susceptibility	1.0931 (0.0917)		1.0189 (0.1921)	
Social Media User Type	1.2669** (0.1113)			0.8281 (0.1564)
SP*TT_Meformer		0.9948 (0.1575)		
SP*TT_Informer		0.9018 (0.1442)		
SP*INFL		1.1516 (0.1234)		
IS*TT_Meformer			0.9759 (0.1912)	
IS*TT_Informer			1.2882 (0.2743)	
IS*INFL			1.2443 (0.1769)	
SMT*TT_Meformer				1.1433 (0.2179)
SMT*TT_Informer				1.6842*** (0.3585)
SMT*INFL				1.5154*** (0.2169)
# of Twitter Followers	0.9991 (0.0006)	0.9989* (0.0006)	0.9992 (0.0006)	0.9987** (0.0006)

# of Tweets Sent	0.9686** (0.0134)	0.9720** (0.0136)	0.9717** (0.0130)	0.9691** (0.0138)
Indie Preference	1.2186** 0.1213	1.2225** (0.1210)	1.2569** (0.1258)	1.2753** (0.1264)
Gender	1.4613*** (0.2217)	1.4817*** (0.2209)	1.5403*** (0.2331)	1.4061** (0.2108)
Constant	0.0498*** (0.0237)	0.1386*** (0.0956)	0.1159*** (0.0767)	0.2556* (0.1967)
Wald χ^2	93.65***	88.47***	92.28***	105.05***
		*****p < 0.01**	****p < 0.05**	***p < 0.10**

Table 17 shows the results of this analysis when the moderating factors are introduced. Key to this analysis is the effect of the moderators: *social presence*, *influence susceptibility*, and *social media user type* (SP, IS, and SMT). As neither Influence Susceptibility nor Social Presence appears to have any significance impact on the two main effects, Tweet Type (*Meformer/Informer*) and Influence, we see no support emerge at this point for H4 or H5. However, there is significant interaction between SM User Type and Informer Tweet Type as well as between SM User Type and Influence, lending support to H6. However, we note that the introduction of interaction effects for Influence reduces the significance of the main effect.

The demographic indicators had significant impacts on FOLLOW. We notice a negative impact of users' self-reported number of twitter followers and number of tweets sent on FOLLOW. Additionally, users' preference for indie vs. mainstream musicians as well as their gender have a positive impact on FOLLOW.

To further examine the effect of Tweet Type on Twitter user preference, we evaluated interactions between preference for specific genre with *Meformer* and *Informer*

Tweet Types. While we found no significance with *Meformer*, interactions with choice by genre and *Informer* Tweet Types were found to be significant.

Given that we see an effect of SM User Type on FOLLOW, we examine the impact of each individual type in our model. These results are presented in Table 18. From this we can see significance when the *socializer* SM User Type is moderating Informer Tweet Types as well as Influence's effect on FOLLOW. In addition, we find a significant interaction between the *information seeker* SM User Type and Influence. No effect for *status seeking* SM User Type was found in this analysis.

Table 18. SMT Effects on FOLLOW

Dependent Variable: FOLLOW				
	Model 5	**Model 6**	**Model 7**	**Model 8**
Independent Variable	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**
TT_Meformer	1.0429 (0.2180)	1.0267 (0.2210)	1.0482 (0.2256)	1.0550 (0.2198)
TT_Informer	0.1201*** (0.0739)	0.5488 (0.2688)	0.4009 (0.2365)	0.1155*** (0.0712)
Influence	0.5943 (0.2741)	1.6824 (0.6018)	0.6752 (0.2915)	0.3298** (0.1752)
ARTIST_POP	1.4045* (0.2864)	1.4008* (0.2791)	1.4050* (0.2819)	1.4087* (0.2896)
ARTIST_ROCK	0.4848*** (0.1138)	0.4870*** (0.1119)	0.4844*** (0.1120)	0.4824*** (0.1141)
ARTIST_COUNTRY	1.5601** (0.3159)	1.5545** (0.3076)	1.5607** (0.3111)	1.5663** (0.3199)
ARTIST_RAP	BASELINE; OMITTED			
TT_Informer*POP	1.9811* (0.7732)	1.8542* (0.6914)	1.8902* (0.7128)	1.9941* (0.7840)
TT_Informer*ROCK	2.2130* (0.9501)	2.1933** (0.9022)	2.2083* (0.9177)	2.2253* (0.9613)
TT_Informer*RAP	1.6995	1.5972	1.6250	1.7080

	(0.6630)	(0.5953)	(0.6125)	(0.6711)
SMT_social	0.8834 (0.0878)			0.8770 (0.0955)
SMT_social* TT_Informer	1.5646*** (0.1980)			1.5682*** (0.1981)
SMT_social*INFL	1.3729*** (0.1601)			1.2901** (0.1623)
SMT_status		1.0718 (0.1161)		
SMT_status* TT_Informer		1.0794 (0.1445)		
SMT_status*INFL		1.0793 (0.1378)		
SMT_info			0.9747 (0.0716)	1.0100 (0.0724)
SMT_info* TT_Informer			1.1141 (0.1148)	
SMT_info*INFL			1.2840*** (0.1188)	1.2033** (0.1176)
# of Twitter Followers	0.9987** (0.0006)	0.9991 (0.0006)	0.9990* (0.0006)	0.9987** (0.0006)
# of Tweets Sent	0.9691** (0.0137)	0.9723** (0.0129)	0.9713** (0.0133)	0.9670** (0.0139)
Indie Preference	1.3294*** 0.1315	1.2047** (0.1196)	1.1823* (0.1189)	1.2972*** (0.1290)
Gender	1.4177** (0.2091)	1.4789*** (0.2247)	1.3963** (0.2127)	1.3766** (0.2033)
Constant	0.1859*** (0.0957)	0.1175*** (0.0532)	0.1691*** (0.0783)	0.1989*** (0.1040)
Wald χ^2	105.05***	86.45***	95.34***	112.38***
		*****p < 0.01**	****p < 0.05**	***p < 0.10**

4.5.3. Intention to "Retweet"

Main Effects

The same evaluations for FOLLOW were conducted for the DV representing a user's self-reported intention to retweet messages from the musicians evaluated in this experiment (RETWEET). Table 19 presents the marginal means for each treatment across all four artists of interest (ARTIST_POP, ARTIST _ROCK, ARTIST _COUNTRY, ARTIST _RAP) as well as the overall DV (RETWEET). These cell means for RETWEET are aggregated and presented graphically in Figure 5. From these means and the F-tests, there is initial evidence that, like that for FOLLOW, Influence has a significant effect on RETWEET providing initial support for H2b. However, once again, the F-tests and means do not appear to show significance for Tweet Type or any apparent interactions between Tweet Type and Influence, leading to a further potential lack of support for H1 and H3.

Table 19. Marginal Means of the Effect of TT and INF on RETWEET

ARTIST_POP				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	3.5761	3.6635	3.4000	**0.43**
	Negative	**Positive**		**F**
Influence (INF)	3.1024	4.0606		**28.85*** **
ARTIST_ROCK				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	2.8466	2.9192	2.6327	**0.65**
	Negative	**Positive**		**F**
Influence (INF)	2.4388	3.2412		**25.18*** **

ARTIST_COUNTRY				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	3.7148	3.6019	3.7018	**0.13**
	Negative	**Positive**		**F**
Influence (INF)	3.3482	4.0170		**11.77*** **
ARTIST_RAP				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	3.0080	2.5596	2.9782	**2.88***
	Negative	**Positive**		**F**
Influence (INF)	2.4400	3.3006		**27.22*** **
RETWEET (Total)				
	Meformer	**Informer**	**Mixed**	**F**
Tweet Type (TT)	3.2864	3.1861	3.1782	**0.62**
	Negative	**Positive**		**F**
Influence (INF)	2.8324	3.6548		**83.61*** **
		***** p < 0.01**	**** p < 0.05**	*** p < 0.10**

Figure 5. Effect of TT and INF on RETWEET for All Artists

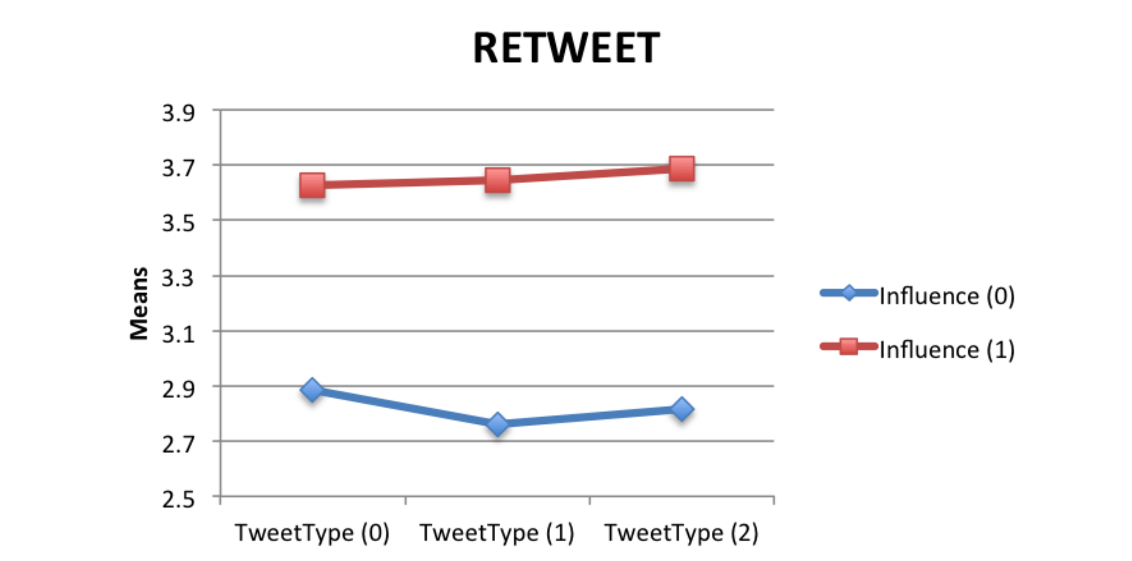


Table 20 reports the results of the GEE in a stepwise manner, utilizing the main effects of interest: *Tweet Type* (*Meformer* and *Informer*), *Influence*, and the interaction effect (TTxINF). Based on the significant Wald χ^2 from all the models in this analysis (Tables 20-22), there is an indication of a progressive and significant fit for all of the models evaluating the effect on RETWEET.

Table 20. Analysis: Main Effects, Interaction on RETWEET

Dependent Variable: RETWEET				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Independent Variable	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**
TT_Meformer	1.1143 (0.1900)		1.0223 (0.1638)	1.0736 (0.2286)
TT_Informer	1.0079 (0.1855)		0.9575 (0.1638)	0.9484 (0.2169)
Influence		2.2762*** (0.2552)	2.2715*** (0.2553)	2.3886*** (0.6693)
TT_Meformer * INFL				0.9020 (0.2887)

TT_Informer * INFL				1.0133 (0.3495)
ARTIST_POP	2.0349*** (0.2224)	2.0349*** (0.2224)	2.0349*** (0.2224)	2.0349*** (0.2224)
ARTIST_ROCK	0.9706 (0.1061)	0.9706 (0.1061)	0.9706 (0.1061)	0.9706 (0.1061)
ARTIST_COUNTRY	2.2563*** (0.2466)	2.2563*** (0.2466)	2.2563*** (0.2466)	2.2563*** (0.2466)
ARTIST_RAP	BASELINE; OMITTED			
Constant	16.52046*** (2.5205)	11.6904*** (1.2077)	11.7224*** (1.8832)	11.4786*** (2.2174)
Wald χ^2	102.75***	155.84***	156.16***	156.45***
		*****p < 0.01**	****p < 0.05**	***p < 0.10**

Individual preference plays a significant role in all of the models once again. But the main interest of this study is the positive significant odds ratios for the main effect of Social Influence. Model 2 demonstrates Influence increasing RETWEET by 127.6%. Models 3 and 4 demonstrate similar levels of the effect of Influence on RETWEET, lending strong support for H2b. Once again, there is no demonstrated impact of either Tweet Type or any significant interaction effect (TT x INF). Based on these observations, we can conclude there is no support for H1b or H3b at this point. However, the continued significance of Influence in the presence of the interaction gives further support to H2b.

Interactions and Moderators

Table 21. Analysis: Main Effects, Moderators, Interactions on RETWEET				
Dependent Variable: RETWEET				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Independent Variable	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**
TT_Meformer	1.1158 (0.1663)	1.2352 (0.5414)	0.9419 (0.3907)	0.8737 (0.4405)

TT_Informer	0.7127 (0.1534)	0.4326* (0.2068)	0.2594*** (0.1209)	0.2408** (0.1370)
Influence	2.1596*** (0.2291)	1.7143** (0.4831)	1.2174 (0.3625)	1.2413 (0.4371)
ARTIST_POP	1.7046*** (0.2235)	1.7046*** (0.2235)	1.7046*** (0.2235)	1.7046*** (0.2235)
ARTIST_ROCK	0.8145 (0.1068)	0.8145 (0.1068)	0.8145 (0.1068)	0.8145 (0.1068)
ARTIST_COUNTRY	2.0357*** (0.2669)	2.0357*** (0.2669)	2.0357*** (0.2669)	2.0357*** (0.2669)
ARTIST_RAP	BASELINE; OMITTED			
TT_Informer*POP	1.7691** (0.4164)	1.7691** (0.4164)	1.7691** (0.4164)	1.7691** (0.4164)
TT_Informer*ROCK	1.7591** (0.4140)	1.7591** (0.4140)	1.7591** (0.4140)	1.7591** (0.4140)
TT_Informer*RAP	1.3930 (0.3279)	1.3930 (0.3279)	1.3930 (0.3279)	1.3930 (0.3279)
Social Presence	1.0696 (0.0463)	1.0742 (0.1151)		
Influence Susceptibility	1.1261** (0.0674)		0.9880 (0.1232)	
Social Media User Type	1.1080* (0.0664)			1.0022 (0.1285)
SP* TT_Meformer		0.9738 (0.1088)		
SP* TT_Informer		1.1481 (0.1335)		
SP*INFL		1.0704 (0.0782)		
IS* TT_Meformer			1.0483 (0.1404)	
IS* TT_Informer			1.4152** (0.2044)	
IS*INFL			1.2226** (0.1187)	
SMT* TT_Meformer				1.0691 (0.1433)

SMT* TT_Informer				1.3454** (0.1971)
SMT*INFL				1.1715* (0.1112)
# of Twitter Followers	0.9986*** (0.0004)	0.9984*** (0.0004)	0.9989*** (0.0004)	0.9986*** (0.0004)
# of Retweets Sent	1.0217* (0.0127)	1.0284** (0.0129)	1.0218* (0.0127)	1.0246** (0.0127)
Indie Preference	1.2260*** 0.0846	1.2396*** (0.1210)	1.2754*** (0.0884)	1.2552*** (0.0883)
Gender	1.2504** (0.1336)	1.2136* (0.1299)	1.2832** (0.1359)	1.1874* (0.1266)
Constant	2.9032*** (0.8943)	5.6863*** (2.6483)	6.7516*** (2.9411)	7.1579*** (3.7334)
Wald χ^2	224.62***	215.81***	229.95***	224.74***
		*****p < 0.01**	****p < 0.05**	***p < 0.10**

Table 21 shows the results of this analysis when the moderating factors are introduced. Unlike the analysis for FOLLOW, we find a significant moderating effect of Influence Susceptibility and SM User Type on both Informer Tweet Type and Influence, offering support for H4 and H6. We observe no significant interaction between Social Presence and either main effect (Tweet Type or Influence); given this lack of significance, we see no support emerge for H5.

We again notice a negative impact of users' self-reported number of Twitter followers on RETWEET. Additionally, the number of retweets sent by users as well as their preference for indie vs. mainstream musicians and gender all have a positive impact on RETWEET.

Similar to FOLLOW, we observe an interaction effect of SM User Type with Informer Tweet Type and Influence’s impact on RETWEET, giving support to H6. Based on this significance, we examine the impact of each individual SM User Type in our model, the results of which are presented in Table 22. The *socializer* SM User Type moderates Informer Tweet Type on RETWEET (p-value = 0.09). In addition, we find a moderately significant interaction between the *information seeker* SM User Type and Influence (p-value = 0.09). As for FOLLOW, no effect for *status seeking* SM User Type was found in this analysis.

Table 22. SMT Effects on RETWEET			
Dependent Variable: RETWEET			
	Model 5	**Model 6**	**Model 7**
Independent Variable	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**	**Exp(b) (Std. Error)**
Meformer	1.0886 (0.1603)	1.0749 (0.1589)	1.0922 (0.1601)
Informer	0.2239*** (0.0926)	0.2833*** (0.1062)	0.2585*** (0.1131)
Influence	1.0405 (0.3610)	1.2400 (0.3788)	0.9234 (0.3293)
ARTIST_POP	1.7046*** (0.2235)	1.7046*** (0.2235)	1.7046*** (0.2235)
ARTIST_ROCK	0.8145 (0.1068)	0.8145 (0.1068)	0.8145 (0.1068)
ARTIST_COUNTRY	2.0357*** (0.2669)	2.0357*** (0.2669)	2.0357*** (0.2669)
ARTIST_RAP	BASELINE; OMITTED		
Informer*POP	1.7691** (0.4164)	1.7691** (0.4164)	1.7691** (0.4164)
Informer*ROCK	1.7591** (0.4140)	1.7591** (0.4140)	1.7591** (0.4140)
Informer*RAP	1.3930 (0.3279)	1.3930 (0.3279)	1.3930 (0.3279)
Influence Susceptibility	1.0216 (0.0906)	0.9846 (0.0828)	1.0093 (0.0783)
IS*Informer	1.2401** (0.4164)	1.3539*** (0.1676)	1.3658*** (0.1446)

IS*INFL	1.1862* (0.1321)	1.2322** (0.1421)	1.1861** (0.1176)
SMT_social	1.0013 (0.0765)		
SMT_social* TT_Informer	1.1551* (0.1149)		
SMT_social*INFL	1.0628 (0.0971)		
SMT_status		1.0654 (0.0828)	
SMT_status* TT_Informer		1.0134 (0.1095)	
SMT_status*INFL		0.9858 (0.0990)	
SMT_info			1.0256 (0.0491)
SMT_info* TT_Informer			1.0217 (0.0709)
SMT_info*INFL			1.0871* (0.0684)
# of Twitter Followers	0.9988*** (0.0004)	0.9989*** (0.0004)	0.9989*** (0.0004)
# of Retweets Sent	1.0192* (0.0126)	1.0222* (0.0127)	1.0225* (0.0126)
Indie Preference	1.3014*** 0.0905	1.2698*** (0.0880)	1.2569*** (0.0869)
Gender	1.2648** (0.1335)	1.2787** (0.1352)	1.2540** (0.1326)
Constant	5.9746*** (2.0980)	5.9210*** (1.8994)	6.0182*** (2.0576)
Wald χ^2	236.90***	231.81***	238.83***
	$***p < 0.01$	**$**p < 0.05$**	**$*p < 0.10$**

4.6. Key Findings and Conclusion

Based on the observations of the data, we summarize our findings for this study in Table 23.

Table 23. Summary of Hypotheses and Findings	
Hypothesis	**Results**
H1 Tweet Type drives Twitter behavior	Partially supported. *Meformer* and *Informer* had no significant main effect on FOLLOW or RETWEET. Informer Tweet Type had a significant main effect when moderated by IS and SMT
H2 Social Influence drives Twitter Behavior	Supported. Influence had a significant effect on both FOLLOW and RETWEET
H3 Twitter Interactions	Not supported
H4 Influence Susceptibility	Supported. IS was found to have a moderating effect on Influence and Informer Tweet Type for FOLLOW and RETWEET
H5 Social Presence	Not Supported
H6 SMS User Type	Supported. SMT was found to have a moderating effect on Influence and Informer Tweet Type for FOLLOW and RETWEET

The goal of this study was to evaluate similar constructs to those employed on the Facebook SMS in Chapter 3 on the leaner, less experiential Twitter microblogging SMS; examining the effects of social influencers and different message-types on the decision-making process of the biggest user base for SMS in general. From this we were able to demonstrate how consumers would respond and connect with independent digital musicians from differing genres on Twitter.

Once again, personal preference for music genres remains a driver of choice for indie musicians. Self-reported preference for different genres and the decision to follow specific artists and retweet messages from that artist that fall into the corresponding genres were found to be significant across all of our models, preliminary analysis, and final examination.

We also see social influence again come to the forefront of impacting user decision-making. Social influence on Twitter, when presented in a positive manner shows an approximate 109% and 128% increase in a student's decision to follow and retweet messages from a musician, respectively. However we do see social media user type moderate the effect of Influence on his/her decision to follow a musician.

Beyond personal preference and social influence, we see *Informer* tweets have an impact on both the user's decision to Follow and their intention to retweet messages from the producer. However, this impact is only present in the presence of moderating factors. *Informer* tweets had an effect on Follow when moderated by social media user type, specifically the users seeking a social experience. This makes intuitive sense, *informer* tweets are those that contain actionable information regarding the content producer, which provides information to the user and allows them to more directly engage with the producer and/or their content. As for intention to retweet, *informer* tweets had an effect when moderated by influence susceptibility as well as the socializer user type.

As before, we social presence has limited moderating effect. We have now observed lack of a moderating effect of this variable across two studies. This lends further credence to an overarching assertion of this dissertation: that the rules change for consumers when we shift from a traditional e-commerce setting into *social commerce*.

The intention driving this study was to further examine the means by which independent digital content producers can leverage the powerful messaging tools of SMS. By using the mechanisms and accepted norms and constructs of the networks, these content producers can gain a foothold in an increasingly diverse and densely populated marketplace. This is especially true of our subject group of interest, digital musicians.

Which makes the lack of support for the effect of the *Meformer* Tweet Type (*Meformer*/*Informer*) in this context surprising, as it appears to drive right to the heart of the *social commerce* experience on Twitter (Java et al. 2007; Naaman et al. 2010; Rui and Whinston 2011; Shi et al. 2011). One possible explanation is the nature of this construct given the self-expressed way in which users engage on Twitter. Additionally, this study, as well as the study in Chapter 3, examined these effects at the profile level, aggregating the content and evaluating messaging and influences on how user's perceive and report intended interactions with these musicians as a whole. Evaluating the effect of messaging types and strategies at the individual message level may shine some light on how they affect musicians' effectiveness on Twitter. We explore this further in Chapter 5.

This study has demonstrated positive main effect of social influences and the moderated effect of Tweet Types on users' decision to follow digital content producers on the Twitter Social Media Site as well as redistribute their content. Across the previous two studies we have demonstrated that these influencers are a key factor impacting behavior and decision-making on two divergent SMS. While we again observe this impact of social influencers on consumer decision-making, we must still consider the impact of personal preference and established behaviors. This study further poses the question of the power of one's peers when the medium changes from direct personal interaction into digital personal interaction, specifically in relation to electronic *social commerce*. Future studies can begin to extend these findings to examine these effects at different levels of the profiles for digital content producers on these Social Media Sites, expanding the discussion to focus more directly on producer-side measures, rounding out the discussion so we can more effectively understand the unique market attributes that define this medium.

Chapter 5

"I HOPE THAT SOMEONE GETS MY MESSAGE IN A BOTTLE": TWEET-LEVEL EFFECTS ON USER PREFERENCE FOR MUSICIANS ON TWITTER

5.1. Introduction

In Chapter 4 we examined messaging types and constructs unique to Twitter that digital content producers, specifically independent digital musicians, could employ to more effectively reach and engage broad bases of users that could potentially become consumers of their digital goods (Ansari et al. 2011). By leveraging these dense networks of users that communicate with one another, the outreach that producers could potentially have redefines even what we've come to know as "traditional" electronic commerce mechanisms, falling under the moniker of *social commerce* (Clemons et al. 2002; Stephen and Toubia 2010).

This exploratory study extends the analysis of the previous two chapters. In Chapters 3 and 4 we examined how digital content producers engage with consumers on SMS and what factors bring consumers to actively engage with and consume the content digital musicians put on these SMS. These studies were conducted via survey experiments with university undergraduate students, thus having a strong focus on the demand-side of *social commerce*. The purpose of this study is to examine similar effects and SMS mechanisms presented in Chapters 3 and 4 more from the producer-side of *social commerce*, testing these constructs empirically, based less on projected, self-reported behavior, and more on observed, recorded behavior. Utilizing data sets collected on Twitter from the four musicians evaluated in the survey experiments delineated in Chapters 3 and 4, we aim to answer the following research questions: (1) Does messaging type and message content on Twitter positively impact user engagement with digital content producers? And (2) what specific Twitter message mechanisms impact dissemination of a content producer's messages?

5.2. Hypotheses

Twitter has four main mechanisms for disseminating user created content that cover both social and broadcasting features: (1) a "tweet," being the initial 140-character message sent out by the content producer, (2) a "retweet," being an active rebroadcasting of the content producers' original message, (3) "following" a user, which subscribes your account to their message feed, allowing you to receive broadcast tweets and engage with them and their other respective followers—being a similar function to Facebook's "friend" but less consequential action—and (4) "favoriting" a tweet sent by a user—being similar to Facebook's "Like" while again having fewer far-reaching consequences than the "Like."

The distinction between the Twitter mechanisms and their Facebook analogues lies in the amount of information offered to direct and indirect networks of users. On Facebook, by default, when you friend users or "Like" their content, this action gets broadcast out to your network of friends as well as your friends' network of friends. Twitter, while it does offer this information, does so in a less overt way. If a user chooses to follow another user, this information gets added to an individual's profile page, but other users must actively seek out this information by directly navigating to a specific list on a user's profile page. Burying information even a few clicks deep on any web page or service is often too cumbersome for everyday users to actually evaluate; meaning this information, while available, is not regularly examined by these normal users which would potentially mitigate any impacts on decision-making that this would have for normal users (Granka et al. 2004; Huberman et al. 2008; Huberman et al. 1998). The same holds for “favoriting” a tweet. Your choice to do so is available, but it is buried several clicks deep. However, the information on how often a message is favorited, similar to how many Likes something accrues on Facebook, is of interest to a content producer. This metric is fairly new in the Twitter API, but has the potential to gain traction with users, which should pique the interest of researchers.

While these differences are important for user engagement purposes at the individual decision-making level, this has been examined in both Chapters 3 and 4 for profile-level decisions. The focus for this study is on the specific decisions users make based on individual messages. Information regarding the activity of Twitter users is fairly easily accessed. This has strong implications for producers broadcasting and engaging with their followers on Twitter. While the individual profile information is readily accessible regarding the number of followers for a producer, the number of retweets and favorites for messages from that producer are buried a few clicks deep and are only displayed at the individual message level. This access to information speaks to the previously discussed social contagion and WOM aspects of consumption on SMS (Aral and Walker 2011a; Aral and Walker 2011b; Dwyer 2007; Hennig-Thurau et al. 2004; Jansen et al. 2009).

Building off of constructs employed in Chapter 4, evaluation of messages posted on Twitter feeds and Facebook timelines has identified several different categories of messages from which can be derived two distinct types of message poster, defined by a need for peer approval and/or attention (Naaman et al. 2010; Rui and Whinston 2011):

meformers, identified by a personal, colloquial, conversational tone to their messages (eg. "Our new album is selling out! Our fans are awesome") and *informers*, identified by a distinctly informational context to their messages (ex. "My new album comes out on _______, preorder your copy at ___________") (Naaman et al. 2010). These types of messages appeal directly to different types of SMS users with different usage patterns. Recall that previous research has shown that 80% of the users whose messages analyzed fell into the *meformer* category leaving the remaining 20% as *informers*. However, *informers* demonstrated, on average, far more friends (mean=131) than *meformers* (mean=42) (Ehrlich and Shami 2010; Kıcıman 2010; Naaman et al. 2010).

On the contrary, behavioral research has shown consumption behavior to be driven by a need for people to enhance their self-concepts and form personal connections with the product, brand, and the producer (Belk 1988; Escalas and Bettman 2005; Richins 1994). This reflects attitudes demonstrated by personal connections people feel toward celebrities and musicians that are often felt by users of SMS; as well as the groups of students originally involved in the discussion that launched this body of research (Donath and Boyd 2004; Sopha and Raghu 2012). As such, we will measure the effect that Tweet Type (*meformer* vs. *informer*) has on the decision-making process of users on the Twitter SMS, specifically their decision to retweet and favorite messages from indie musicians.

H1 (Tweet Type Retweet Hypothesis)

Tweet Type will impact the number of times a message is "retweeted" on Twitter

H2 (Tweet Type Favorite Hypothesis)

Tweet Type will impact the number of times a message is "favorited" on Twitter

We discuss the data gathered for this study in the following section.

5.3. Data

For this study, a sample of tweets from each of the four artists examined and profiled in Chapters 3 and 4 was collected by querying the Twitter API. Every day at 12:01am, a Python script grabbed and stored in XML the collection of the previous day's tweets and some descriptive statistics from a list of independent artist's Twitter feeds; this list was assembled through examination of the last ten years of monthly Billboard "Top 100" charts for independent musicians. These tweet collections contained a great deal of tagging metadata, which is largely irrelevant to our study. Of interest were the following variables listed in Table 24, which we utilized in our regressions.

Table 24. Variables of Interest

Variable Name	Description	Type/Coding
tweet_type	The descriptive nature of the message in a tweet	Binary 0 = meformer 1 = informer
retweet_count	The number of times this tweet has been retweeted	Continuous
follower_count	The number of followers for the musician at the time the tweet was sent	Continuous
favorite_count	The number of times this tweet has been favorited	Continuous
rt	Was this tweet originally a retweet?	Binary 0 = No 1 = Yes
hashtag	Does this tweet contain a hashtag?	Binary 0 = No 1 = Yes
reply	Was this tweet a reply to a follower's tweet?	Binary 0 = No 1 = Yes
url	Does this tweet contain a URL?	Binary 0 = No 1 = Yes
two_week_album_release	Was this tweet sent two weeks before or after an album release?	Binary 0 = No 1 = Yes

Significant changes in the Twitter API (http://dev.twitter.com) as well as in the OAuth authorization framework (http://oauth.net) made collection, consolidation, and cleanup of this database a complex and, ultimately, manual process.[3] For the purposes of this study, we examined <200 (mean: 164) tweets each from all four artist spanning variable periods of time, given the different volume of tweets each of the artists sends out each day, on average. The tweets for each artist were indexed in order of time posted, oldest to newest, the irrelevant metadata was removed and the variables of interest that were not directly provided by the API were coded: tweet_type, rt, hashtag, reply, and url. For tweet_type, we coded the variables in line with the original definitions (Ehrlich and Shami 2010; Kıcıman 2010; Naaman et al. 2010).

To ensure our coding for *tweet_type* was valid, we sent a selection of 10-20 tweets to five different researchers, unaffiliated with this study. In addition to the tweets themselves, the researchers were sent definitions for *meformer* and *informer* and instructions to code each tweet in line with these definitions. Their opinions regarding the tweets matched ours with 99% consistency, validating our coding.

Given that the decision to follow these artists have already been made by the community of users, we do not evaluate any potential influence effects in this study; nor do we evaluate any changes in *follower_count* as our dependent variable. While it may be worthwhile to evaluate the effects these Twitter-specific mechanisms have on numbers of followers for digital content producers, it is out of scope for this particular analysis.

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[3] Moving forward with this more robust tweet database, we will examine more reliable and future-proof means of querying the Twitter API

Descriptive statistics for this study are presented in Table 25.

Table 25. Descriptive Statistics				
	ARTIST 1 (POP)	**ARTIST 2 (ROCK)**	**ARTIST 3 (COUNTRY)**	**ARTIST 4 (RAP)**
N	176	133	167	183
Tweets Per Day				
Min	1	1	1	4
Max	8	20	3	61
Mean	1.517	5.783	1.285	13.071
Hours Between Tweets				
Min	0.02	0.01	0.03	0.01
Max	929.73	75.9	354.15	18.02
Mean	55.498	4.934	53.452	1.178
Median	20.635	0.17	26.75	0.07
Tweet Type				
0 = Meformer	87 (49%)	111 (83%)	134 (80%)	147 (80%)
1 = Informer	89 (51%)	22 (17%)	33 (20%)	36 (20%)
Retweet Count				
Min	0	0	0	0
Max	170	29	56	11
Mean	21.79	2.61	7.62	0.415
Median	16	1	4	0
Favorite Count				
Min	0	0	0	0
Max	87	23	40	5
Mean	12.15	2.3	5.47	0.306
Median	9	1	3	0
Follower Count				
Min	6960	65601	27059	2247
Max	37419	68442	31288	2305
Mean	19739.5	66937.76	28438.63	2281.22
Median	17967	66992	28092	2281
Delta	30459	2841	4229	58
Message is a Retweet?				
0 = No	176 (100%)	39 (29%)	166 (>99%)	183 (100%)
1 = Yes	0 (0%)	94 (71%)	1 (<1%)	0 (0%)
Message Has a Hashtag?				
0 = No	109 (62%)	72 (54%)	137 (82%)	178 (97%)
1 = Yes	67 (38%)	61 (46%)	30 (18%)	5 (3%)

Message is a Reply? **0 = No** **1 = Yes**	162 (92%) 14 (8%)	38 (29%) 95 (71%)	153 (92%) 14 (8%)	50 (27%) 133 (73%)
Message Has a URL? **0 = No** **1 = Yes**	29 (16%) 147 (84%)	93 (70%) 40 (30%)	54 (32%) 113 (68%)	134 (73%) 49 (27%)

There are patterns of usage that emerge in this initial examination of the descriptive statistics. Artists 2 and 4 tweet significantly more each day than 1 and 3; Artist 1 creates a balance between *meformer* and *informer* messaging, while 2-4 tend to heavily engage their followers with *meformer* tweets; artist 1 appears to have significantly more messages retweeted by their followers, as well as garnering more favorites for their tweets than 2-4, with artist 3 coming in a distant second. These differences for artist 1 and, to a lesser extent artist 3, may stem from the fact that their collected tweets span the largest time period, >1 year, while artists 2 and 4 have their tweets collected over a period of a few months; differentiated by the volume in which they tweet each day. This can be confirmed in the delta for follower count; artists 1 and 3 saw increases in followers proportional to their number of total followers and respective time periods, while artists 2 and 4 saw fewer in number of new followers for a proportional number of tweets sent.

There are also patterns of engagement from the producer side of the relationships, as evidenced by the covariates in our study. Artist 2 was the only musician that actively retweeted content sent by their followers, they also demonstrated, similar to artist 4, a sense of direct engagement with their fans by actively replying to a significantly greater proportion of their messages.

Also of note here are the low number of hashtags (#) in the messages sent by any of these artists. The hashtag is a mechanism used on quick message sites to organize content around a specific subject. For example, the Arab Spring uprising of late 2010-early 2011 utilized the hashtag “#arabspring” to create a movement on Twitter. This metric can be tracked easily through the Twitter service and analytics tools. When a subject reaches critical mass and the related specific hashtag is repeated by enough users, it is said to be “trending” on Twitter, denoting an importance of the subject in a global sense (McGuinness 2012). Some of the lack of momentum for the artists in our study may be related to not effectively nor repeatedly employing the hashtag in the tweets to their followers. Thought this may only be a circumstantial observation.

5.4. Results and Analysis

Table 26 offers the correlation matrices for each of the variables we have used in this evaluation of the data for each of the four musicians in our analysis. We find little indication of multicollinearity. We find a few instances of moderate levels of correlation between IVs, hashtag and reply. After observing both variables separately, reply has been omitted from our regressions.

Table 26. Correlation Matrix

	V1	**V2**	**V3**	**V4**	**V5**	**V6**	**V7**	**V8**
V1 Retweet Count	1							
V2 Favorite Count	0.700	1						
V3 Tweet Type	0.321	0.118	1					

V4 Hours Between	0.214	0.383	0.055	1				
V5 Is Retweet?	-0.185	-0.176	-0.203	-0.149	1			
V6 Has Hashtag?	0.179	0.028	0.177	0.019	0.145	1		
V7 Is Reply?	-0.395	-0.395	-0.433	-0.275	0.497	-0.139	1	
V8 Has URL?	0.300	0.342	0.407	0.224	-0.236	0.139	-0.659	1
V9 Two Weeks	0.085	-0.069	0.120	-0.101	0.409	0.231	0.111	-0.064
V10 Four Weeks	0.063	-0.092	0.147	-0.135	0.574	0.351	0.135	-0.062
V11 Follower Count	-0.045	0.044	-0.095	0.023	0.720	0.282	0.072	-0.050

	V9	**V10**	**V11**
V9 Two Weeks			
V10 Four Weeks	0.691	1	
V11 Follower Count	0.387	0.613	1

For this analysis, we employed Poisson regression, grouped by artist, to examine the effects of tweet_type, on the two major “Twitter mechanisms” (retweet_count, favorite_count) of interest serving as DVs, and our collection of covariates (rt, hashtag, url).[4]

Table 27. Analysis: Effects on Retweet and Favorite Count		
	DV: RETWEET_COUNT	**DV: FAVORITE_COUNT**
Independent Variable	**Coef. (Std. Error)**	**Coef. (Std. Error)**
Tweet Type	0.4675*** (0.0314)	-0.0671* (0.0393)
Hours Between Tweets	0.0005*** (0.0001)	0.0003** (0.0001)
Is RT?	-1.2327*** (0.1118)	-1.2035*** (0.1117)
Has Hashtag?	0.1006*** (0.0301)	-0.1477*** (0.0419)
Has URL?	0.1657*** (0.0374)	0.5841*** (0.0491)
Follower Count	0.0001*** (3.00e-06)	0.0001*** (3.41e-06)
Two Week Window	0.2684*** (0.0405)	-0.0772 (0.0679)
Wald χ^2	665.27***	1032.56***
	*****p < 0.01**	****p < 0.05 *p < 0.10**

Table 27 presents the results of our analysis. Of immediate notice is the significance of Tweet Type for both DVs. For Retweet Count we see the significance of informer Tweet Type, while *meformer* tweets were found to be moderately significant on Favorite Count. Thus we find support for both H1 and H2. We see also that the hours between tweets have a slight impact on both Retweet and Favorite Count, the more time

[4] We utilized the Stata 12 statistical package and the `xtpoisson` command with the `fe` option to run fixed effects models

between tweets sent, the more they seem to impact the producer's community of followers.

We also see interesting effects of our covariates, the norms employed in message behavior and content on Twitter. We find that tweets which are themselves retweeted by the producers are, in turn, retweeted and favorited less by their followers. As for the specific content matters themselves, messages that contain URLs have a positive impact on both Retweet and Favorite Count while tweets that contain hashtags have a positive impact on Retweet Count but a negative impact on Favorite Count. Finally, tweets sent within a two-week time window of the release of new digital content, in this case a new album, were found to have a positive effect on Retweet Count but no significant impact on Favorite Count.

The magnitude of some of the coefficients may call into question the overall impact of these factors, but their significance in the models is worth noting and examining. This could very well be due to the small number of followers reported for artist 4, as well as the very small delta in followers for the sample collected for this analysis. Perhaps with a dataset encompassing a greater time horizon, we may see more robust results from these effects measuring a similar time period, as opposed to measuring a similar number of messages sent.

5.5. Key Findings and Conclusion

The regressions in this study demonstrate the significant main effect of *tweet_type* on the message-level metrics of *retweet_count* and *favorite_count*. We observe effects of the Twitter mechanics on their respective DVs across all artists. Based on these observations of the data, we summarize our findings in Table 28.

Table 28. Summary of Hypotheses and Findings	
Hypothesis	**Results**
H1 Tweet Type impacts Retweet Count	Supported
H2 Tweet Type impacts Favorite Count	Supported

This study's goal was to evaluate effects at the individual message-level similar to the profile-level effects examined in Chapter 5. The focus also shifted from explicitly examining consumer, demand-side behavior to allowing the active producer-side behavior to come more into focus for the analysis. From this study, we were able to begin observing how independent digital musicians are utilizing the strategies explored in this research to be able to more effectively connect with, and drive consumption of their presence and content on modern SMS.

The key piece of this analysis was the message-level effect of Tweet Type, *meformer* or *informer*, on the various effective measures of success on the Twitter SMS. In Chapter 5 we found significant effects of informer tweets on either a user's self-reported intention to retweet messages or their desire to follow a specific musician on Twitter when moderated by influence susceptibility and/or consumer social media user type. From the analysis in this chapter we found a significant impact of the informer Tweet Type on the number of times a message was retweeted, consistent with the results of the study in Chapter 5, as well as a significant effect of the *meformer* Tweet Type on the number of times a message is favorited.

In this study we also examined the effect of important Twitter mechanisms and any potential effects that may be found therein. We see significance in most all of the factors evaluated in our analysis. We see a positive effect on the number of times a message is retweeted as well as favorited if the message contains a URL. This makes good intuitive sense; as the students originally interviewed when this research originally began, they want to be able to sample content provided by these musicians. There is a difference with tweets that contain a hashtag. Here we see a positive effect on Retweet Count but a negative effect on Favorite Count. Given the way that hashtags are employed on Twitter, these results are consistent. Hashtags are denoted to have a topic begin trending among users, to be the center of a discussion. As such, they are intended to be included in messages that are to be retweeted among the community of users. We would not necessarily see these messages be favorited, per se, but we can safely anticipate a significant effect on Retweet Count. An exploration of possible interactions between these factors may reveal more information.

Of particular interest are the effect that the time, in hours, between tweets sent by producers as well as if the message from the producers is a retweet of a message from another Twitter user has on Retweet and Favorite Count. There is a positive effect of hours between tweets on both DVs, the implication of which is that the more time that exists between tweets sent from digital content producers, the greater the number of times the message is retweeted and favorited by consumers. In tandem with this is the negative significance found on both DVs if the original message from the producer was, itself, a retweet of another user's message. Both of these factors seem to imply a "tweet overload" effect that exists among Twitter users. It would appear that if users are inundated by messages from a particular producer, they might begin to feel that they have already seen and resent enough messages from this producer. The danger here is that the message will simply be skipped over in its entirety, defeating the purpose of digital content producers tweeting to their followers.

The magnitude of some of the coefficients cause one to question the overall impact of some of the factors in this analysis, but their significance warrants further examination, potentially with a more robust or Twitter dataset. The potential for variance that is unaccounted for is likely due to the nature of the tweets collected from artist 4. Given that their behavior is significantly different from the other musicians observed in this analysis, specifically in the number and type of tweets they send out to their followers, sending more per day and tweets that significantly more colloquial than informative. While their behavior may be enough to account for the diminished effects compared to their peers, it is more likely that the shorter time horizon for their data is the culprit. Further exploration of this is needed.

The intention behind this study was to examine the message-level effects of the content and mechanisms used on the Twitter SMS that we have been examining at the profile-level in the studies found in Chapters 4 and 5. Additionally, this study was intended to begin empirically examining if the effects we have been evaluating in the studies preceding this one have any real world analogue. With an examination of these effects in their proper context, outside of an experimental setting, we develop a greater level of confidence in our assertions regarding social commerce and SMS usage. More importantly, we can extend this analysis and these findings into a more robust discussion of the actual effect of the unique SMS features and mechanisms, allowing us to create a rich discussion on how digital content producers and consumers of their media can more effective navigate the evolving market value chain found in 21st Century social media.

Chapter 6

SUMMARY AND CONCLUSIONS

6.1. Summary of Findings and Implications

This dissertation, over the course of three studies, sought to explore the effect of various social influencers, message content, and personal preferences on Social Media Sites with diametrically opposed user experiences and engagement. The extant body of Information Systems research regarding SMS has not fully explored the experience from the perspective of increasing a user's hedonic utility, specifically surrounding *social commerce* for digital experience goods. This dissertation begins to fill a gap in the body of research by exploring the specific measures (unique to SMS and their impact on *social commerce*) that can further shorten the value chain between independent digital content producers and their potential consumers.

The key assertion driving this exploration is that the decision-making process that drives engagement with producers and hedonic consumption of digital goods on SMS, like Facebook and Twitter, follows a different set of rules than it does on traditional web sites, portals, and e-commerce outlets. The implications of this research are (1) that personal preference, of course, still has an impact on choice; (2) *a posteriori* peer influence, irrespective of *a priori* susceptibility of said influence, has an impact on choice; (3) positive informational influences, in the form of professional product reviews, impacts choice; (4) social influences, in general, have an impact on choice on both passive- and active-engagement SMS; and (5) while message content appears to have a moderated impact on choice for profile-level decision-making, there is a clear direct impact on choice at the message-level. The findings in this research lay the foundation for establishing a solid strategy to drive engagement and potential sales and consumption of the digital goods created by independent content producers. This research also sets up exploration of future research in a truly unique way on a rapidly evolving medium.

In this dissertation, we offered three studies in the context of passive-engagement SMS (Facebook) and active-engagement SMS (Twitter), the latter at profile and individual message levels. In Chapter 3, the first study demonstrated the positive effects of informational and peer influences on a specific user's decision to "Like" digital content producers on Facebook. We demonstrated that these influencers, despite the effect of personal preference, are an essential factor impacting behavior and choice on SMS. However, this study demonstrates that we must continue to consider the importance of personal preference and established behaviors. Ultimately, this study brings to focus the discussion into the power of one's peers when the medium changes from direct personal interaction into digital personal interaction, specifically in relation to electronic *social commerce*.

The second study, found in Chapter 4, demonstrated the positive effect of social influences on an individual user's decision to follow as well as redistribute messages and content, via retweets, from digital goods producers on the Twitter SMS. This study served to examine user interaction with these content producers at the profile-level, examining the aggregate effect of examining multiple messages and profile information on the decision-making process. This study also examined the effect of different message types on the DVs of interest, finding no significant effect at this level of analysis. Similar to the Chapter 3 study, this experiment examined the effects of these effects as we move from the experience-rich Facebook SMS to the experience-lean Twitter microblogging SMS.

Chapter 5 offered the final study of this dissertation, demonstrating the significant effect of message type, from Chapter 4, at the individual message-level on the Twitter SMS. The implication of this finding being that we see positive and negative impacts of message types sent by content producers, for different DVs, at the individual message-level, which we did not directly observe when the messages and profile was examined in the aggregate (Chapter 4). This empirical evaluation of a real-world set of tweets from the same four musicians of divergent styles examined in Chapters 3 and 4 also provided us an opportunity to begin exploring the effect of message mechanics and constructs unique to the Twitter SMS, finding initial significance that merits exploration with a dataset with a greater longitudinal time horizon. This exploration allows us to create a rich discussion on how content producers and consumers can generate messaging strategies to more effectively navigate the evolving market found in 21st Century social media.

6.2. Future Research

This study opens the door to several avenues of future research that could (1) further explore the fundamental message and content mechanisms and constructs for modern SMS, including the meaning of “Like,” further examination of the impact of “retweets,” and other Twitter message constructs (hashtags, urls, favorites), and portal design for experience rich SMS; (2) SMS integration with other services of differing and similar foci, such as: Spotify, YouTube, Instagram, Tumblr, etc.; and (3) the organizational benefits of hedonic consumption on SMS, specifically the idea of social gamification. There is also the potential for developing a small-scale social media API for use in controlled experiments for narrow focus on the items evaluated in this dissertation, as well as the proposed future research items. The findings of this and future research in this area could help us gain a more fundamental examination of *social commerce*, as we see greater and more robust integration of SMS and mechanisms into traditional e-commerce portals.

In conclusion, this dissertation has demonstrated that Social Media Sites, specifically in terms of the evolving market structure that is *social commerce*, are a solid base for continuing information systems research. Given the rapidly changing landscape of both e-commerce and social media, there is merit in researchers giving this subject greater scrutiny, specifically in offering strategies for independent digital content producers, allowing the niche markets to finally grasp the market power prophesied in early 2000's Long Tail research. Most importantly, further and deeper exploration in this area can allow us to more effectively understand producer and user behavior as well as the unique market attributes that define this rapidly evolving medium.

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APPENDIX A: IRB APPROVALS

IRB Exemption Approval for Chapter 3 Survey

Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Raghu Santanam BA
From:	Mark Roosa, Chair Soc Beh IRB
Date:	09/05/2012
Committee Action:	**Exemption Granted**
IRB Action Date:	09/05/2012
IRB Protocol #:	1208008200
Study Title:	Influence and Decision Making for Independent Musicians on Facebook

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

IRB Exemption Approval for Chapter 4 Survey

ASU Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Raghu Santanam BA
From:	Mark Roosa, Chair Soc Beh IRB
Date:	11/26/2012
Committee Action:	**Exemption Granted**
IRB Action Date:	11/26/2012
IRB Protocol #:	1211008554
Study Title:	Influence and Messaging for Independent Musicians on Twitter

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

APPENDIX B: INFLUENCE IMPACT ON DECISION-MAKING ON FACEBOOK SURVEY

Dear Participant,

We are a group of researchers from the Department of Information Systems at the W. P. Carey School of Business. As part of an ongoing research program on social networking and digital entertainment products, we are conducting a research study to evaluate **user preferences and choices regarding independent musicians on the Facebook social network.** We are requesting your participation in this study, which will take approximately 25 minutes of your time.

Your responses to the survey will be used to determine factors that help users make decisions regarding entertainers and musicians on Facebook. There are no foreseeable risks or discomforts for your participation.

Your participation in this study is voluntary. You may skip questions if you wish. If you choose not to participate or withdraw from the study at any time, there will be no penalty. You must be 18 or older to participate in the study.

Your responses will be anonymous. The results of this study may be used in reports, presentations, or publications, but your identity will not be known. Results will only be shared in the aggregate form.

If you have any questions concerning the research study, please contact the research team using the contact information provided below. If you have any questions about your rights as a subject/participant in this research, of if you feel you have been placed at risk, you may contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788.

Submission of the survey will be considered your consent to participate.

Sincerely,

Matthew Sopha, Ph.D. Candidate
Department of Information Systems
W. P. Carey School of Business, Arizona State University
msopha@asu.edu

Raghu Santanam, Ph.D.
Department of Information Systems
W. P. Carey School of Business, Arizona State University
raghu.santanam@asu.edu

Genre Preference

_______	Rock	_______	Pop	_______	Rap/Hip-Hop	_______	Country
_______	Heavy Metal	_______	Soundtracks	_______	Soul/Funk	_______	Folk
_______	Alternative	_______	Classical	_______	Electronic/Dance	_______	Religious
_______	Blues	_______	Jazz	_______	Other		

Please circle the number which best represents your preference		Only Popular Artists	Mostly Popular Artists	Popular and Indie Evenly	Mostly Independent Artists	Only Independent Artists
1	I tend to listen to:	1	2	3	4	5

Facebook

Number of Facebook "friends" (approximate if you are not completely certain) __________

Number of hours a week spent on Facebook (approximate if you are not completely certain)_________

PLEASE WAIT UNTIL PROMPTED TO PROCEED TO THE NEXT PAGE

Based on what you have seen/heard, would you choose to Like this artist?

Artist # ______ Like ______No

Briefly state why or why not:

Please circle the number which best represents your level of agreement or disagreement with the following statements: "I will likely …"		Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
1	Say positive things about this artist to other people.	1	2	3	4	5	6	7
2	Encourage my friends and relatives to listen to this artist.	1	2	3	4	5	6	7
3	Listen to this artist over the next few months.	1	2	3	4	5	6	7
4	Recommend this artist to someone who seeks my advice.	1	2	3	4	5	6	7
5	Consider listening to this artist as my first choice.	1	2	3	4	5	6	7

One of the Comments I Saw for this Artist Was:

_________ "I like their incorporation of instruments and a solid beat"

_________ "Too indie, boring"

PLEASE WAIT UNTIL PROMPTED TO PROCEED TO THE NEXT PAGE

Please circle the number which best represents your level of agreement or disagreement with the following statements: “When I “Like” something on Facebook/Spotify …”		Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
1	It is important that others like the same thing.	1	2	3	4	5	6	7
2	I generally like and follow things that I think others will approve of.	1	2	3	4	5	6	7
3	If other people can see me listening to or following a musician, I often ensure it is an artist they expect me to listen to.	1	2	3	4	5	6	7
4	I achieve a sense of belonging by listening to the same music and following the same things that others do.	1	2	3	4	5	6	7
5	If I want to be like someone, I often try to listen to the same music and follow the same things on Facebook.	1	2	3	4	5	6	7
6	To make sure I find the right music/musicians, I often observe who others are following/listening to.	1	2	3	4	5	6	7
7	If I have little experience with a musician, I often ask my friends about them.	1	2	3	4	5	6	7
8	I often consult other people to help choose other artists that are similar.	1	2	3	4	5	6	7
9	I frequently gather information from friends or family about a musician before I listen to them.	1	2	3	4	5	6	7

	Please circle the number which best represents your level of agreement or disagreement with the following statements: "When I log on to Facebook …"	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
1	There is a sense of human contact.	1	2	3	4	5	6	1
2	There is a sense that I can connect with Facebook friends on a personal level.	1	2	3	4	5	6	2
3	My interactions with Facebook friends bring us closer together.	1	2	3	4	5	6	3
4	I feel that my interactions with Facebook friends are emotional.	1	2	3	4	5	6	4
5	There is a sense of human sensitivity.	1	2	3	4	5	6	5

Choose All of the Following that Apply

"When I click 

on a person/company's Facebook page..."

__________ My LIKE gets registered on the person/company's Facebook page

__________ My LIKE gets posted on my Facebook wall

__________ By default, my LIKE gets posted on my friends' timelines

__________ I get updates on my timeline from that person/company

__________ By default, my LIKE gets posted on the timelines of friends of friends

__________ I get money from the person/company I chose to LIKE

Demographics

Please put an X next to the item that best represents your response to the following questions:

1. Gender: (a) _____Male (b)_____Female

2. Age: ________ years (please specify)

3. Ethnicity: (a) _____Caucasian (b)_____African-American (c)_____Hispanic (d)_____Indian

   (e)_____Asian (f)_____Native American (g)_____Other

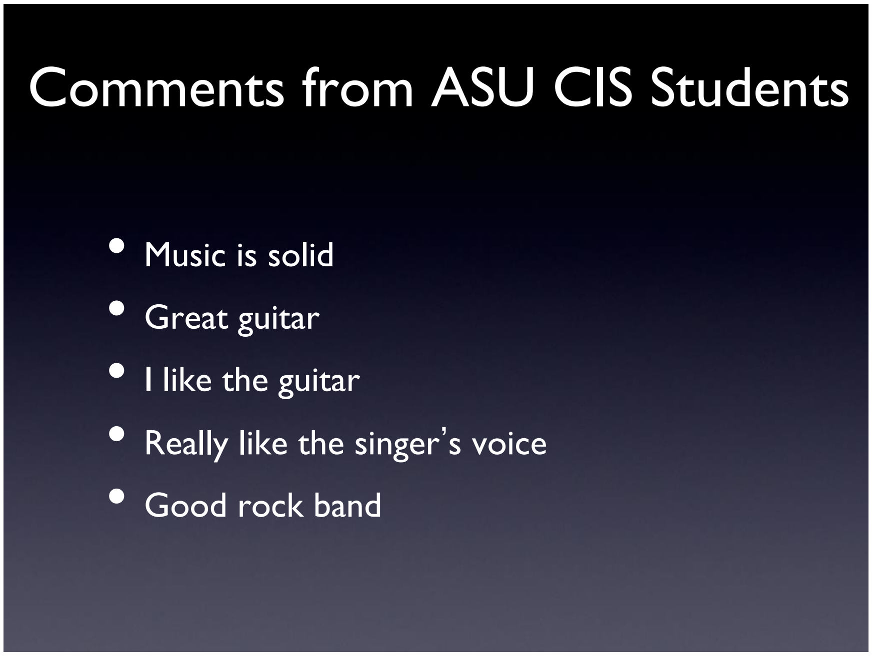
4. Do you, or have you ever, regularly practiced playing a musical instrument? _____Yes _____ No

5. Have you ever played in a band or other musical ensemble? _____Yes _____ No

YOU HAVE COMPLETED THE SURVEY. THANK YOU!

APPENDIX C: SAMPLE COMMENTS FROM FACEBOOK STUDY

Figure 6. Sample Positive and Negative Peer Comments (Artist 2 – Rock)



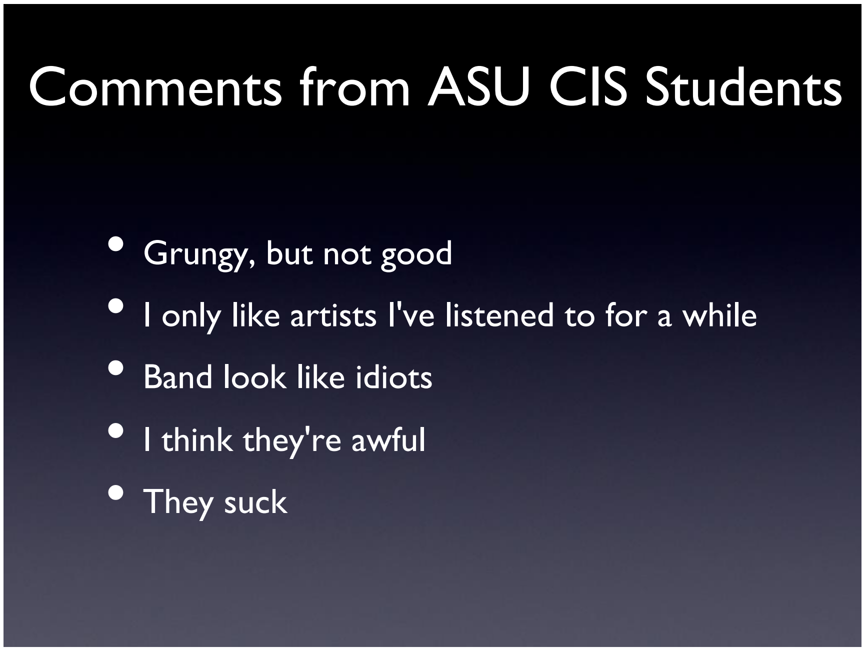
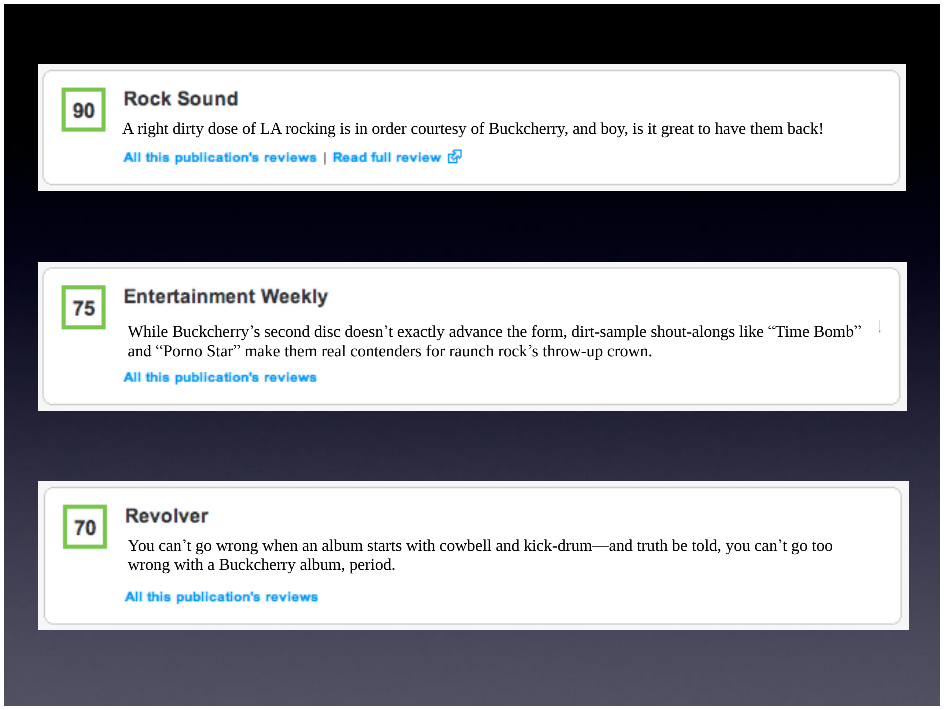


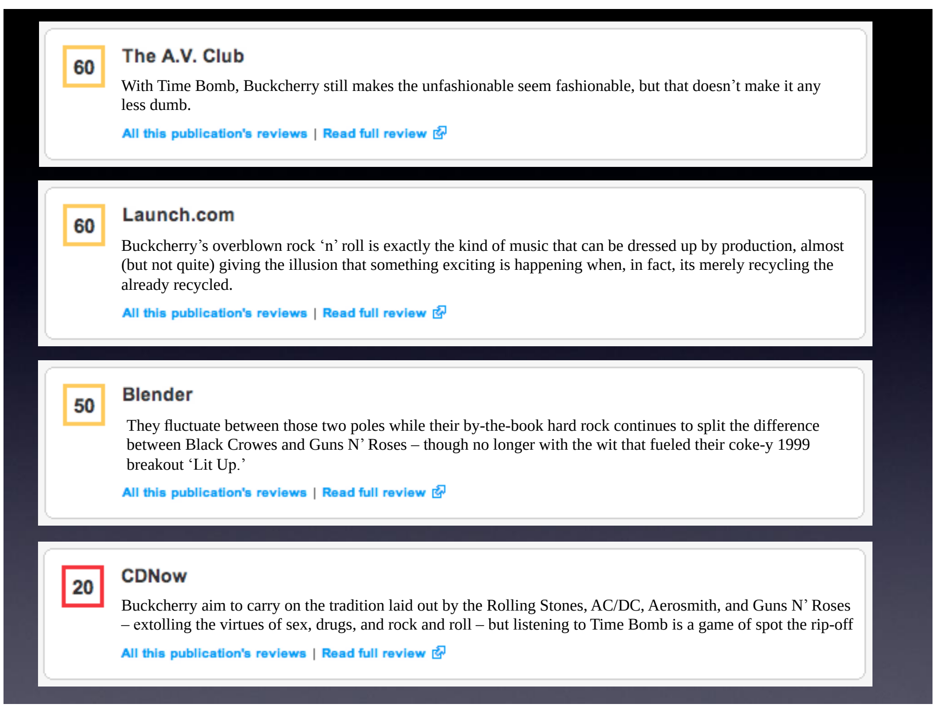
Figure 7. Sample Positive and Negative Information Comments (Artist 2 – Rock)



90 **Rock Sound**
A right dirty dose of LA rocking is in order courtesy of Buckcherry, and boy, is it great to have them back!
All this publication's reviews | Read full review

75 **Entertainment Weekly**
While Buckcherry's second disc doesn't exactly advance the form, dirt-sample shout-alongs like "Time Bomb" and "Porno Star" make them real contenders for raunch rock's throw-up crown.
All this publication's reviews

70 **Revolver**
You can't go wrong when an album starts with cowbell and kick-drum—and truth be told, you can't go too wrong with a Buckcherry album, period.
All this publication's reviews



60 **The A.V. Club**
With Time Bomb, Buckcherry still makes the unfashionable seem fashionable, but that doesn't make it any less dumb.
All this publication's reviews | Read full review

60 **Launch.com**
Buckcherry's overblown rock 'n' roll is exactly the kind of music that can be dressed up by production, almost (but not quite) giving the illusion that something exciting is happening when, in fact, its merely recycling the already recycled.
All this publication's reviews | Read full review

50 **Blender**
They fluctuate between those two poles while their by-the-book hard rock continues to split the difference between Black Crowes and Guns N' Roses – though no longer with the wit that fueled their coke-y 1999 breakout 'Lit Up.'
All this publication's reviews | Read full review

20 **CDNow**
Buckcherry aim to carry on the tradition laid out by the Rolling Stones, AC/DC, Aerosmith, and Guns N' Roses – extolling the virtues of sex, drugs, and rock and roll – but listening to Time Bomb is a game of spot the rip-off
All this publication's reviews | Read full review

APPENDIX D: TWITTER TYPES AND INFLUENCE SURVEY

Dear Participant,

We are a group of researchers from the Department of Information Systems at the W. P. Carey School of Business. As part of an ongoing research program on social networking and digital entertainment products, we are conducting a research study to evaluate **user preferences and choices regarding independent musicians on the Twitter social network.** We are requesting your participation in this study, which will take approximately 30 minutes of your time.

Your responses to the survey will be used to determine factors that help users make decisions regarding entertainers and musicians on Twitter. There are no foreseeable risks or discomforts for your participation.

Your participation in this study is voluntary. You may skip questions if you wish. If you choose not to participate or withdraw from the study at any time, there will be no penalty. You must be 18 or older to participate in the study.

Your responses will be anonymous. The results of this study may be used in reports, presentations, or publications, but your identity will not be known. Results will only be shared in the aggregate form.

If you have any questions concerning the research study, please contact the research team using the contact information provided below. If you have any questions about your rights as a subject/participant in this research, of if you feel you have been placed at risk, you may contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480) 965-6788.

Submission of the survey will be considered your consent to participate.

Sincerely,

Matthew Sopha, Ph.D. Candidate
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Raghu Santanam, Ph.D.
Department of Information Systems
W. P. Carey School of Business, Arizona State University
raghu.santanam@asu.edu

Genre Preference (Rank your preference, 1 – highest, 4 – lowest)

_______ Rock _______ Pop _______ Rap/Hip-Hop _______ Country

	Please circle the number which best represents your preference	Only Popular Artists	Mostly Popular Artists	Popular and Indie Evenly	Mostly Independent Artists	Only Independent Artists
1	I tend to listen to:	1	2	3	4	5

Twitter (approximate responses if you are not completely certain)

Number of users you "follow" on Twitter _________

Number of Twitter "followers" you have _________

Number of hours a day spent reading Tweets ________

Number of Tweets you send in a typical day ________

Number of messages you Retweet in a typical day ________

Number of musicians you follow (names?) ________

PLEASE WAIT UNTIL PROMPTED TO PROCEED TO THE NEXT PAGE

Based on what you have seen/heard, would you choose to Follow **this artist?**

Artist #| ______ Follow ______No

Briefly state why or why not:

Please circle the number which best represents your level of agreement or disagreement with the following statements: “I will likely …”		Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
1	Tweet positive messages about this artist.	1	2	3	4	5	6	7
2	Encourage my friends and relatives to listen to this artist.	1	2	3	4	5	6	7
3	Retweet messages from this artist.	1	2	3	4	5	6	7
4	Listen to this artist over the next few months.	1	2	3	4	5	6	7
5	Recommend this artist to someone who seeks my advice.	1	2	3	4	5	6	7

One of the Tweets I Saw About this Artist Said:

_________ “I like their incorporation of instruments and a solid beat”

_________ “Too indie, boring”

PLEASE WAIT UNTIL PROMPTED TO PROCEED TO THE NEXT PAGE

	Please circle the number which best represents your level of agreement or disagreement with the following statements: "When I Follow someone on Twitter …"	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
1	It is important that my friends Follow the same person.	1	2	3	4	5	6	7
2	I generally like and follow things that I think others will approve of.	1	2	3	4	5	6	7
3	If other people can see me listening to or following a musician, I often ensure it is an artist they expect me to listen to.	1	2	3	4	5	6	7
4	I achieve a sense of belonging by listening to the same music and following the same people that others do.	1	2	3	4	5	6	7
5	If I want to be like someone, I often try to listen to the same music and follow the same people on Twitter.	1	2	3	4	5	6	7
6	To make sure I find the right music/musicians, I often observe who others are following/listening to.	1	2	3	4	5	6	7
7	If I have little experience with a musician, I often ask my friends about them.	1	2	3	4	5	6	7
8	I often consult other people to help choose other artists that are similar.	1	2	3	4	5	6	7
9	I frequently gather information from friends or family about a musician before I listen to them.	1	2	3	4	5	6	7

Please circle the number which best represents your level of agreement or disagreement with the following statements: "I use social media sites like Twitter …"		Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
1	To get support from my friends and family.	1	2	3	4	5	6	7
2	To meet interesting people.	1	2	3	4	5	6	7
3	To feel like I belong to a community.	1	2	3	4	5	6	7
4	To discuss things with other people.	1	2	3	4	5	6	7
5	To stay in touch with people I know.	1	2	3	4	5	6	7
6	Because I feel pressure from my friends to participate.	1	2	3	4	5	6	7
7	Because it makes me look cool.	1	2	3	4	5	6	7
8	To develop my career through group participation.	1	2	3	4	5	6	7
9	To get information about local events.	1	2	3	4	5	6	7
10	To get information about national events.	1	2	3	4	5	6	7
11	To get useful information about products and services.	1	2	3	4	5	6	7

Please circle the number which best represents your level of agreement or disagreement with the following statements: "When I view my Twitter feed ..."		Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree Nor Disagree	Somewhat Agree	Agree	Strongly Agree
1	There is a sense of human contact.	1	2	3	4	5	6	7
2	There is a sense that I can connect with Twitter followers on a personal level.	1	2	3	4	5	6	7
3	My interactions with Twitter followers bring us closer together.	1	2	3	4	5	6	7
4	I feel that my "conversations" with Twitter followers are emotional.	1	2	3	4	5	6	7
5	There is a sense of human sensitivity.	1	2	3	4	5	6	7

Choose All of the Following that Apply

"When I click Follow on a person/company's Twitter feed…"

__________ My decision to Follow gets registered on the person/company's Twitter page

__________ My decision to Follow gets posted on my Twitter feed

__________ By default, my decision to Follow gets posted on my followers' Twitter feed(s)

__________ I get Tweets on my Twitter feed from that person/company

__________ By default, my decision to Follow gets posted on the Twitter feed of followers of my followers

__________ I get money from the person/company I chose to Follow

Demographics

Please put an X next to the item that best represents your response to the following questions:

1. Gender: (a) _____Male (b)_____Female

2. Age: ________ years (please specify)

3. Ethnicity: (a) _____Caucasian (b)_____African-American (c)_____Hispanic (d)_____Indian

   (e)_____Asian (f)_____Native American (g)_____Other

4. Do you, or have you ever, regularly practiced playing a musical instrument? _____Yes _____ No

5. Have you ever played in a band or other musical ensemble? _____Yes _____ No

YOU HAVE COMPLETED THE SURVEY. THANK YOU!

APPENDIX E: SAMPLE TWEETS FROM TWITTER STUDY

Figure 8. Sample Positive and Negative Peer Tweets (Artist 3 – Country)

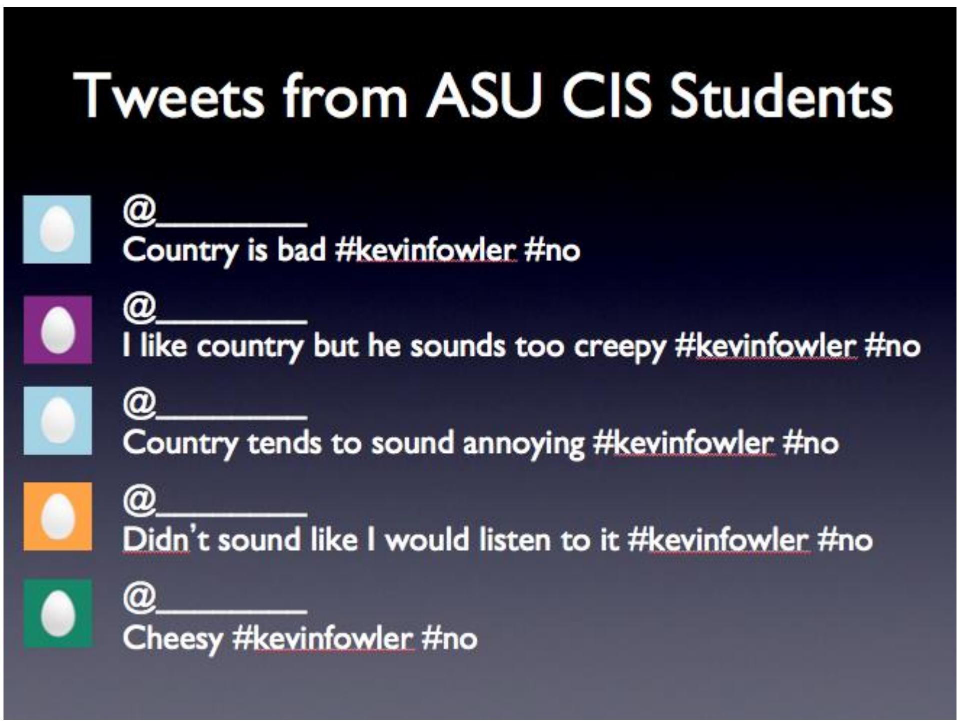

Figure 9. Sample Meformer and Informer Artist Tweets (Artist 3 – Country)